

# PANEL DATA MODELS WITH NONADDITIVE UNOBSERVED HETEROGENEITY: ESTIMATION AND INFERENCE

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**ABSTRACT.** This paper considers fixed effects estimation and inference in linear and nonlinear panel data models with random coefficients and endogenous regressors. The quantities of interest – means, variances, and other moments of the random coefficients – are estimated by cross sectional sample moments of GMM estimators applied separately to the time series of each individual. To deal with the incidental parameter problem introduced by the noise of the within-individual estimators in short panels, we develop bias corrections. These corrections are based on higher-order asymptotic expansions of the GMM estimators and produce improved point and interval estimates in moderately long panels. Under asymptotic sequences where the cross sectional and time series dimensions of the panel pass to infinity at the same rate, the uncorrected estimator has an asymptotic bias of the same order as the asymptotic variance. The bias corrections remove the bias without increasing variance. An empirical example on cigarette demand based on Becker, Grossman and Murphy (1994) shows significant heterogeneity in the price effect across U.S. states.

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## 1. INTRODUCTION

This paper considers estimation and inference in linear and nonlinear panel data models with random coefficients and endogenous regressors. The quantities of interest are means, variances, and other moments of the distribution of the random coefficients. In a state level panel model of rational addiction, for example, we might be interested in the mean and variance of the distribution of the price effect on cigarette consumption across states, controlling for endogenous past and future consumptions. These models pose important challenges in estimation and inference if the relation between the regressors and individual coefficients is left unrestricted. Fixed effects methods based on GMM estimators applied separately to the time series of each individual can be severely biased due to the incidental parameter problem. The source of the bias is the finite-sample bias of GMM if some of the regressors is endogenous or the model is nonlinear in parameters, or nonlinearities if the parameter of interest is the variance or other high order moment of the individual coefficients. Neglecting the heterogeneity and imposing fixed coefficients does not solve the problem, because the resulting estimators are generally inconsistent for the mean of the random coefficients (Yitzhaki, 1996, and Angrist, Graddy and Imbens, 2000).<sup>1</sup> Moreover, imposing fixed coefficients does not allow us to estimate other moments of the distribution of the random coefficients.

We introduce a class of bias-corrected panel fixed effects GMM estimators. Thus, instead of imposing fixed coefficients, we estimate different coefficients for each individual using the time series observations and correct for the resulting incidental parameter bias. For linear models, in addition to the bias correction, these estimators differ from the standard fixed effects estimators in that both the intercept and the slopes are different for each individual. Moreover, unlike for the classical random coefficient estimators, they do not rely on any restriction in the relationship between the regressors and random coefficients; see Hsiao and Pesaran (2004) for a recent survey on random coefficient models. This flexibility allows us to account for Roy (1951) type selection where the regressors are decision variables with levels determined by their returns. Linear models with Roy selection are commonly referred to as correlated random coefficient models in the panel data literature. In the presence of endogenous regressors, treating the random coefficients as fixed effects is also convenient to overcome the identification problems in these models pointed out by Kelejian (1974).

The most general models we consider are semiparametric in the sense that the distribution of the individual coefficients is unspecified and the parameters are identified from moment conditions. These conditions can be nonlinear functions in parameters and variables, accommodating both linear and nonlinear random coefficient models, and allowing for the presence of time varying endogeneity in the regressors not captured by the individual coefficients. We

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<sup>1</sup>Heckman and Vytlacil (2000) and Angrist (2004) find sufficient conditions for fixed coefficient OLS and IV estimators to be consistent for the average coefficient.

use the moment conditions to estimate the model parameters and other quantities of interest via GMM methods applied separately to the time series of each individual. The resulting estimates can be severely biased in short panels due to the incidental parameters problem, which in this case is a consequence of the finite-sample bias of GMM (Newey and Smith, 2004) and/or the nonlinearity of the quantities of interest in the individual coefficients. We develop analytical corrections to reduce the bias.

To derive the bias corrections, we use higher-order expansions of the GMM estimators, extending the analysis in Newey and Smith (2004) for cross sectional estimators to panel data estimators with fixed effects and serial dependence. If  $n$  and  $T$  denote the cross sectional and time series dimensions of the panel, the corrections remove the leading term of the bias of order  $O(T^{-1})$ , and center the asymptotic distribution at the true parameter value under sequences where  $n$  and  $T$  grow at the same rate. This approach is aimed to perform well in econometric applications that use moderately long panels, where the most important part of the bias is captured by the first term of the expansion. Other previous studies that used a similar approach for the analysis of linear and nonlinear fixed effects estimators in panel data include, among others, Kiviet (1995), Phillips and Moon (1999), Alvarez and Arellano (2003), Hahn and Kuersteiner (2002), Lancaster (2002), Woutersen (2002), Hahn and Newey (2004), and Hahn and Kuersteiner (2011). See Arellano and Hahn (2007) for a survey of this literature and additional references.

A first distinctive feature of our corrections is that they can be used in overidentified models where the number of moment restrictions is greater than the dimension of the parameter vector. This situation is common in economic applications such as rational expectation models. Overidentification complicates the analysis by introducing an initial stage for estimating optimal weighting matrices to combine the moment conditions, and precludes the use of the existing methods. For example, Hahn and Newey's (2004) and Hahn and Kuersteiner's (2011) general bias reduction methods for nonlinear panel data models do not cover optimal two-step GMM estimators. A second distinctive feature is that our results are specifically developed for models with multiple nonadditive heterogeneity, whereas the previous studies focused mostly on models with additive heterogeneity captured by an scalar individual effect. Exceptions include Arellano and Hahn (2006) and Bester and Hansen (2008), which also considered multiple heterogeneity, but they focus on parametric likelihood-based panel models with exogenous regressors. Bai (2009) analyzed related linear panel models with exogenous regressors and multidimensional interactive individual effects. Bai's nonadditive heterogeneity allows for interaction between individual effects and unobserved factors, whereas the nonadditive heterogeneity that we consider allows for interaction between individual effects and observed regressors. A third distinctive feature of our analysis is the focus on moments of the distribution of the individual effects as one of the main quantities of interest.

We illustrate the applicability of our methods with empirical and numerical examples based on the cigarette demand application of Becker, Grossman and Murphy (1994). Here, we estimate a linear rational addictive demand model with state-specific coefficients for price and common parameters for the other regressors using a panel data set of U.S. states. We find that standard estimators that do not account for non-additive heterogeneity by imposing a constant coefficient for price can have important biases for the common parameters, mean of the price coefficient and demand elasticities. The analytical bias corrections are effective in removing the bias of the estimates of the mean and standard deviation of the price coefficient. Figure 1 gives a preview of the empirical results. It plots a normal approximation to the distribution of the price effect based on uncorrected and bias corrected estimates of the mean and standard deviation of the distribution of the price coefficient. The figure shows that there is important heterogeneity in the price effect across states. The bias correction reduces by more than 15% the absolute value of the estimate of the mean effect and by 30% the estimate of the standard deviation.

Some of the results for the linear model are related to the recent literature on correlated random coefficient panel models with fixed  $T$ . Graham and Powell (2008) gave identification and estimation results for average effects. Arellano and Bonhomme (2010) studied identification of the distributional characteristics of the random coefficients in exogenous linear models. None of these papers considered the case where some of the regressors have time varying endogeneity not captured by the random coefficients or the model is nonlinear. For nonlinear models, Chernozhukov, Fernández-Val, Hahn and Newey (2010) considered identification and estimation of average and quantile treatment effects. Their nonparametric and semiparametric bounds do not require large- $T$ , but they do not cover models with continuous regressors and time varying endogeneity.

The rest of the paper is organized as follows. Section 2 illustrates the type of models considered and discusses the nature of the bias in two examples. Section 3 introduces the general model and fixed effects GMM estimators. Section 4 derives the asymptotic properties of the estimators. The bias corrections and their asymptotic properties are given in Section 5. Section 6 describes the empirical and numerical examples. Section 7 concludes with a summary of the main results. Additional numerical examples, proofs and other technical details are given in the online supplementary appendix Fernández-Val and Lee (2012).

## 2. MOTIVATING EXAMPLES

In this section we describe in detail two simple examples to illustrate the nature of the bias problem. The first example is a linear correlated random coefficient model with endogenous regressors. We show that averaging IV estimators applied separately to the time series of each individual is biased for the mean of the random coefficients because of the finite-sample bias

of IV. The second example considers estimation of the variance of the individual coefficients in a simple setting without endogeneity. Here the sample variance of the estimators of the individual coefficients is biased because of the non-linearity of the variance operator in the individual coefficients. The discussion in this section is heuristic leaving to Section 4 the specification of precise regularity conditions for the validity of the asymptotic expansions used.

**2.1. Correlated random coefficient model with endogenous regressors.** Consider the following panel model:

$$(2.1) \quad y_{it} = \alpha_{0i} + \alpha_{1i}x_{it} + \epsilon_{it}, \quad (i = 1, \dots, n; t = 1, \dots, T);$$

where  $y_{it}$  is a response variable,  $x_{it}$  is an observable regressor,  $\epsilon_{it}$  is an unobservable error term, and  $i$  and  $t$  usually index individual and time period, respectively.<sup>2</sup> This is a linear random coefficient model where the effect of the regressor is heterogenous across individuals, but no restriction is imposed on the distribution of the individual effect vector  $\alpha_i := (\alpha_{0i}, \alpha_{1i})'$ . The regressor can be correlated with the error term and a valid instrument  $(1, z_{it})$  is available for  $(1, x_{it})$ , that is  $E[\epsilon_{it} | \alpha_i] = 0$ ,  $E[z_{it}\epsilon_{it} | \alpha_i] = 0$  and  $Cov[z_{it}x_{it} | \alpha_i] \neq 0$ . An important example of this model is the panel version of the treatment-effect model (Wooldridge, 2002 Chapter 10.2.3, and Angrist and Hahn, 2004). Here, the objective is to evaluate the effect of a treatment ( $D$ ) on an outcome variable ( $Y$ ). The average causal effect for each level of treatment is defined as the difference between the potential outcome that the individual would obtain with and without the treatment,  $Y_d - Y_0$ . If individuals can choose the level of treatment, potential outcomes and levels of treatment are generally correlated. An instrumental variable  $Z$  can be used to identify the causal effect. If potential outcomes are represented as the sum of permanent individual components and transitory individual-time specific shocks, that is  $Y_{jit} = Y_{ji} + \epsilon_{jit}$  for  $j \in \{0, 1\}$ , then we can write this model as a special case of (2.1) with  $y_{it} = (1 - D_{it})Y_{0it} + D_{it}Y_{1it}$ ,  $\alpha_{0i} = Y_{0i}$ ,  $\alpha_{1i} = Y_{1i} - Y_{0i}$ ,  $x_{it} = D_{it}$ ,  $z_{it} = Z_{it}$ , and  $\epsilon_{it} = (1 - D_{it})\epsilon_{0it} + D_{it}\epsilon_{1it}$ .

Suppose that we are ultimately interested in  $\alpha_1 := E[\alpha_{1i}]$ , the mean of the random slope coefficient. We could neglect the heterogeneity and run fixed effects OLS and IV regressions in

$$y_{it} = \alpha_{0i} + \alpha_1 x_{it} + u_{it},$$

where  $u_{it} = x_{it}(\alpha_{1i} - \alpha_1) + \epsilon_{it}$  in terms of the model (2.1). In this case, OLS and IV estimate weighted means of the individual coefficients in the population; see, for example, Yitzhaki (1996) and Angrist and Krueger (1999) for OLS, and Angrist, Graddy and Imbens (2000) for IV. OLS puts more weight on individuals with higher variances of the regressor because

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<sup>2</sup>More generally,  $i$  denotes a group index and  $t$  indexes the observations within the group. Examples of groups include individuals, states, households, schools, or twins.

they give more information about the slope; whereas IV weighs individuals in proportion to the variance of the first stage fitted values because these variances reflect the amount of information that the individuals convey about the part of the slope affected by the instrument. These weighted means are generally different from the mean effect because the weights can be correlated with the individual effects.

To see how these implicit OLS and IV weighting schemes affect the estimand of the fixed-coefficient estimators, assume for simplicity that the relationship between  $x_{it}$  and  $z_{it}$  is linear, that is  $x_{it} = \pi_{0i} + \pi_{1i}z_{it} + v_{it}$ ,  $(\epsilon_{it}, v_{it})$  is normal conditional on  $(z_{it}, \alpha_i, \pi_i)$ ,  $z_{it}$  is independent of  $(\alpha_i, \pi_i)$ , and  $(\alpha_i, \pi_i)$  is normal, for  $\pi_i := (\pi_{0i}, \pi_{1i})'$ . Then, the probability limits of the OLS and IV estimators are<sup>3</sup>

$$\begin{aligned}\alpha_1^{OLS} &= \alpha_1 + \{Cov[\epsilon_{it}, v_{it}] + 2E[\pi_{1i}]Var[z_{it}]Cov[\alpha_{1i}, \pi_{1i}]\}/Var[x_{it}], \\ \alpha_1^{IV} &= \alpha_1 + Cov[\alpha_{1i}, \pi_{1i}]/E[\pi_{1i}].\end{aligned}$$

These expressions show that the OLS estimand differs from the average coefficient in presence of endogeneity, i.e. non zero correlation between the individual-time specific error terms, or whenever the individual coefficients are correlated; while the IV estimand differs from the average coefficient only in the latter case.<sup>4</sup> In the treatment-effects model, there exists correlation between the error terms in presence of endogeneity bias and correlation between the individual effects arises under Roy-type selection, i.e., when individuals who experience a higher permanent effect of the treatment are relatively more prone to accept the offer of treatment. Wooldridge (2005) and Murtazashvile and Wooldridge (2005) give sufficient conditions for consistency of standard OLS and IV fixed effects estimators. These conditions amount to  $Cov[\epsilon_{it}, v_{it}] = 0$  and  $Cov[x_{it}, \alpha_{1i}|\alpha_{i0}] = 0$ .

Our proposal is to estimate the mean coefficient from separate time series estimators for each individual. This strategy consists of running OLS or IV for each individual, and then estimating the population moment of interest by the corresponding sample moment of the individual estimators. For example, the mean of the random slope coefficient in the population is estimated by the sample average of the OLS or IV slopes. These sample moments converge to the population moments of interest as number of individuals  $n$  and time periods  $T$  grow. However, since a different coefficient is estimated for each individual, the asymptotic distribution of the sample moments can have asymptotic bias due to the incidental parameter problem (Neyman and Scott, 1948).

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<sup>3</sup>The limit of the IV estimator is obtained from a first stage equation that imposes also fixed coefficients, that is  $x_{it} = \pi_{0i} + \pi_{1i}z_{it} + w_{it}$ , where  $w_{it} = z_{it}(\pi_{1i} - \pi_1) + v_{it}$ . When the first stage equation is different for each individual, the limit of the IV estimator is

$$\alpha_1^{IV} = \alpha_1 + 2E[\pi_{1i}]Cov[\alpha_{1i}, \pi_{1i}]/\{E[\pi_{1i}]^2 + Var[\pi_{1i}]\}.$$

See Theorems 2 and 3 in Angrist and Imbens (1995) for a related discussion.

<sup>4</sup>This feature of the IV estimator is also pointed out in Angrist, Graddy and Imbens (1999), p. 507.

To illustrate the nature of this bias, consider the estimator of the mean coefficient  $\alpha_1$  constructed from individual time series IV estimators. In this case the incidental parameter problem is caused by the finite-sample bias of IV. This can be explained using some expansions. Thus, assuming independence across  $t$ , standard higher-order asymptotics gives (e.g. Rilstone et. al., 1996), as  $T \rightarrow \infty$

$$\sqrt{T}(\hat{\alpha}_{1i}^{IV} - \alpha_{1i}) = \frac{1}{\sqrt{T}} \sum_{t=1}^T \psi_{it} + \frac{1}{\sqrt{T}} \beta_i + o_P(T^{-1/2}),$$

where  $\psi_{it} = E[\tilde{z}_{it}\tilde{x}_{it} \mid \alpha_i, \pi_i]^{-1} \tilde{z}_{it}\epsilon_{it}$  is the influence function of IV,  $\beta_i = -E[\tilde{z}_{it}\tilde{x}_{it} \mid \alpha_i, \pi_i]^{-2} E[\tilde{z}_{it}^2 \tilde{x}_{it}\epsilon_{it} \mid \alpha_i, \pi_i]$  is the higher-order bias of IV (see, e.g., Nagar, 1959, and Buse, 1992), and the variables with tilde are in deviation from their individual means, e.g.,  $\tilde{z}_{it} = z_{it} - E[z_{it} \mid \alpha_i, \pi_i]$ . In the previous expression the first order asymptotic distribution of the individual estimator is centered at the truth since  $\sqrt{T}(\hat{\alpha}_{1i}^{IV} - \alpha_{1i}) \rightarrow_d N(0, \sigma_i^2)$  as  $T \rightarrow \infty$ , where  $\sigma_i^2 = E[\tilde{z}_{it}\tilde{x}_{it} \mid \alpha_i, \pi_i]^{-2} E[\tilde{z}_{it}^2 \epsilon_{it}^2 \mid \alpha_i, \pi_i]$ .

Let  $\hat{\alpha}_1 = n^{-1} \sum_{i=1}^n \hat{\alpha}_{1i}^{IV}$ , the sample average of the IV estimators. The asymptotic distribution of  $\hat{\alpha}_1$  is not centered around  $\alpha_1$  in short panels or more precisely under asymptotic sequences where  $T/\sqrt{n} \rightarrow 0$ . To see this, consider the expansion for  $\hat{\alpha}_1$

$$\sqrt{n}(\hat{\alpha}_1 - \alpha_1) = \frac{1}{\sqrt{n}} \sum_{i=1}^n (\alpha_{1i} - \alpha_1) + \frac{1}{\sqrt{n}} \sum_{i=1}^n (\hat{\alpha}_{1i}^{IV} - \alpha_{1i}).$$

The first term is the standard influence function for a sample mean of known elements. The second term comes from the estimation of the individual elements inside the sample mean. Assuming independence across  $i$  and combining the previous expansions,

$$\sqrt{n}(\hat{\alpha}_1 - \alpha_1) = \underbrace{\frac{1}{\sqrt{n}} \sum_{i=1}^n (\alpha_{1i} - \alpha_1)}_{=O_P(1)} + \underbrace{\frac{1}{\sqrt{T}} \frac{1}{\sqrt{nT}} \sum_{i=1}^n \sum_{t=1}^T \psi_{it}}_{=O_P(1/\sqrt{T})} + \underbrace{\frac{\sqrt{n}}{T} \frac{1}{n} \sum_{i=1}^n \beta_i}_{=O(\sqrt{n}/T)} + o_P(1).$$

This expression shows that the bias term dominates the asymptotic distribution of  $\hat{\alpha}_1$  in short panels under sequences where  $T/\sqrt{n} \rightarrow 0$ . Averaging reduces the order of the variance of  $\hat{\alpha}_{1i}^{IV}$ , without affecting the order of its bias. In this case the estimation of the individual coefficients has no first order effect in the asymptotic variance of  $\hat{\alpha}_1$  because the second term is of smaller order than the first term.

A potential drawback of the individual by individual time series estimation is that it might more be sensitive to weak identification problems than fixed coefficient pooled estimation.<sup>5</sup> In the random coefficient model, for example, we require that  $E[\tilde{z}_{it}\tilde{x}_{it} \mid \alpha_i, \pi_i] = \pi_{1i} \neq 0$  with probability one, i.e., for all the individuals, whereas fixed coefficient IV only requires that this

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<sup>5</sup>We thank a referee for pointing out this issue.

condition holds on average, i.e.,  $E[\pi_{1i}] \neq 0$ . The individual estimators are therefore more sensitive than traditional pooled estimators to weak instruments problems. On the other hand, individual by individual estimation relaxes the exogeneity condition by conditioning on additive and non-additive time invariant heterogeneity, i.e.,  $E[\tilde{z}_{it}\epsilon_{it} \mid \alpha_i, \pi_i] = 0$ . Traditional fixed effects estimators only condition on additive time invariant heterogeneity. A formal treatment of these identification issues is beyond the scope of this paper.

**2.2. Variance of individual coefficients.** Consider the panel model:

$$y_{it} = \alpha_i + \epsilon_{it}, \quad \epsilon_{it} \mid \alpha_i \sim (0, \sigma_\epsilon^2), \quad \alpha_i \sim (\alpha, \sigma_\alpha^2), \quad (t = 1, \dots, T; i = 1, \dots, n);$$

where  $y_{it}$  is an outcome variable of interest, which can be decomposed in an individual effect  $\alpha_i$  with mean  $\alpha$  and variance  $\sigma_\alpha^2$ , and an error term  $\epsilon_{it}$  with zero mean and variance  $\sigma_\epsilon^2$  conditional on  $\alpha_i$ . The parameter of interest is  $\sigma_\alpha^2 = \text{Var}[\alpha_i]$  and its fixed effects estimator is

$$\hat{\sigma}_\alpha^2 = (n-1)^{-1} \sum_{i=1}^n (\hat{\alpha}_i - \hat{\alpha})^2,$$

where  $\hat{\alpha}_i = T^{-1} \sum_{t=1}^T y_{it}$  and  $\hat{\alpha} = n^{-1} \sum_{i=1}^n \hat{\alpha}_i$ .

Let  $\varphi_{\alpha_i} = (\alpha_i - \alpha)^2 - \sigma_\alpha^2$  and  $\varphi_{\epsilon_{it}} = \epsilon_{it}^2 - \sigma_\epsilon^2$ . Assuming independence across  $i$  and  $t$ , a standard asymptotic expansion gives, as  $n, T \rightarrow \infty$ ,

$$\sqrt{n}(\hat{\sigma}_\alpha^2 - \sigma_\alpha^2) = \underbrace{\frac{1}{\sqrt{n}} \sum_{i=1}^n \varphi_{\alpha_i}}_{=O_P(1)} + \underbrace{\frac{1}{\sqrt{T}} \frac{1}{\sqrt{nT}} \sum_{i=1}^n \sum_{t=1}^T \varphi_{\epsilon_{it}}}_{=O_P(1/\sqrt{T})} + \underbrace{\frac{\sqrt{n}}{T} \sigma_\epsilon^2}_{=O(\sqrt{n}/T)} + o_P(1).$$

The first term corresponds to the influence function of the sample variance if the  $\alpha_i$ 's were known. The second term comes from the estimation of the  $\alpha_i$ 's. The third term is a bias term that comes from the nonlinearity of the variance in  $\hat{\alpha}_i$ . The bias term dominates the expansion in short panels under sequences where  $T/\sqrt{n} \rightarrow 0$ . As in the previous example, the estimation of the  $\alpha_i$ 's has no first order affect in the asymptotic variance since the second term is of smaller order than the first term.

### 3. THE MODEL AND ESTIMATORS

We consider a general model with a finite number of moment conditions  $d_g$ . To describe it, let the data be denoted by  $z_{it}$  ( $i = 1, \dots, n; t = 1, \dots, T$ ). We assume that  $z_{it}$  is independent over  $i$  and stationary and strongly mixing over  $t$ . Also, let  $\theta$  be a  $d_\theta$ -vector of common parameters,  $\{\alpha_i : 1 \leq i \leq n\}$  be a sequence of  $d_\alpha$ -vectors with the realizations of the



individual effects, and  $g(z; \theta, \alpha_i)$  be an  $d_g$ -vector of functions, where  $d_g \geq d_\theta + d_\alpha$ .<sup>6</sup> The model has true parameters  $\theta_0$  and  $\{\alpha_{i0} : 1 \leq i \leq n\}$ , satisfying the moment conditions

$$E[g(z_{it}; \theta_0, \alpha_{i0})] = 0, \quad (t = 1, \dots, T; i = 1, \dots, n),$$

where  $E[\cdot]$  denotes conditional expectation with respect to the distribution of  $z_{it}$  conditional on the individual effects.

Let  $\bar{E}[\cdot]$  denote the expectation taken with respect to the distribution of the individual effects. In the previous model, the ultimate quantities of interest are smooth functions of parameters and observations, which in some cases could be the parameters themselves,

$$\zeta = \bar{E}E[\zeta_i(z_{it}; \theta_0, \alpha_{i0})],$$

if  $\bar{E}E|\zeta_i(z_{it}; \theta_0, \alpha_{i0})| < \infty$ , or moments or other smooth functions of the individual effects

$$\mu = \bar{E}[\mu(\alpha_{i0})],$$

if  $\bar{E}|\mu(\alpha_{i0})| < \infty$ . In the correlated random coefficient example,  $g(z_{it}; \theta_0, \alpha_{i0}) = z_{it}(y_{it} - \alpha_{0i0} - \alpha_{1i0}x_{it})$ ,  $\theta = \emptyset$ ,  $d_\theta = 0$ ,  $d_\alpha = 2$ , and  $\mu(\alpha_{i0}) = \alpha_{1i0}$ . In the variance of the random coefficients example,  $g(z_{it}; \theta_0, \alpha_{i0}) = (y_{it} - \alpha_{0i0})$ ,  $\theta = \emptyset$ ,  $d_\theta = 0$ ,  $d_\alpha = 1$ , and  $\mu(\alpha_{i0}) = (\alpha_{1i0} - \bar{E}[\alpha_{1i0}])^2$ .

Some more notation, which will be extensively used in the definition of the estimators and in the analysis of their asymptotic properties, is the following

$$\begin{aligned} \Omega_{ji}(\theta, \alpha_i) &:= E[g(z_{it}; \theta, \alpha_i)g(z_{i,t-j}; \theta, \alpha_i)'], \quad j \in \{0, 1, 2, \dots\}, \\ G_{\theta_i}(\theta, \alpha_i) &:= E[G_\theta(z_{it}; \theta, \alpha_i)] = E[\partial g(z_{it}; \theta, \alpha_i)/\partial \theta'], \\ G_{\alpha_i}(\theta, \alpha_i) &:= E[G_\alpha(z_{it}; \theta, \alpha_i)] = E[\partial g(z_{it}; \theta, \alpha_i)/\partial \alpha_i'], \end{aligned}$$

where superscript  $'$  denotes transpose and higher-order derivatives will be denoted by adding subscripts. Here  $\Omega_{ji}$  is the covariance matrix between the moment conditions for individual  $i$  at times  $t$  and  $t-j$ , and  $G_{\theta_i}$  and  $G_{\alpha_i}$  are time series average derivatives of these conditions. Analogously, for sample moments

$$\begin{aligned} \hat{\Omega}_{ji}(\theta, \alpha_i) &:= T^{-1} \sum_{t=j+1}^T g(z_{it}; \theta, \alpha_i)g(z_{i,t-j}; \theta, \alpha_i)', \quad j \in \{0, 1, \dots, T-1\}, \\ \hat{G}_{\theta_i}(\theta, \alpha_i) &:= T^{-1} \sum_{t=1}^T G_\theta(z_{it}; \theta, \alpha_i) = T^{-1} \sum_{t=1}^T \partial g(z_{it}; \theta, \alpha_i)/\partial \theta', \\ \hat{G}_{\alpha_i}(\theta, \alpha_i) &:= T^{-1} \sum_{t=1}^T G_\alpha(z_{it}; \theta, \alpha_i) = T^{-1} \sum_{t=1}^T \partial g(z_{it}; \theta, \alpha_i)/\partial \alpha_i'. \end{aligned}$$

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<sup>6</sup>We impose that some of the parameters are common for all the individuals to help preserve degrees of freedom in estimation of short panels with many regressors. An order condition for this model is that the number of individual specific parameters  $d_\alpha$  has to be less than the time dimension  $T$ .

In the sequel, the arguments of the expressions will be omitted when the functions are evaluated at the true parameter values  $(\theta'_0, \alpha'_{i0})'$ , e.g.,  $g(z_{it})$  means  $g(z_{it}; \theta_0, \alpha_{i0})$ .

In cross-section and time series models, parameters defined from moment conditions are usually estimated using the two-step GMM estimator of Hansen (1982). To describe how to adapt this method to panel models with fixed effects, let  $\widehat{g}_i(\theta, \alpha_i) := T^{-1} \sum_{t=1}^T g(z_{it}; \theta, \alpha_i)$ , and let  $(\tilde{\theta}', \{\tilde{\alpha}'_i\}_{i=1}^n)'$  be some preliminary one-step FE-GMM estimator, given by  $(\tilde{\theta}', \{\tilde{\alpha}'_i\}_{i=1}^n)' = \arg \inf_{\{(\theta', \alpha'_i)' \in \Upsilon\}_{i=1}^n} \sum_{i=1}^n \widehat{g}_i(\theta, \alpha_i)' \widehat{W}_i^{-1} \widehat{g}_i(\theta, \alpha_i)$ , where  $\Upsilon \subset \mathbb{R}^{d_\theta + d_\alpha}$  denotes the parameter space, and  $\{\widehat{W}_i : 1 \leq i \leq n\}$  is a sequence of positive definite symmetric  $d_g \times d_g$  weighting matrices. The two-step FE-GMM estimator is the solution to the following program

$$(\widehat{\theta}', \{\widehat{\alpha}'_i\}_{i=1}^n)' = \arg \inf_{\{(\theta', \alpha'_i)' \in \Upsilon\}_{i=1}^n} \sum_{i=1}^n \widehat{g}_i(\theta, \alpha_i)' \widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i)^{-1} \widehat{g}_i(\theta, \alpha_i),$$

where  $\widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i)$  is an estimator of the optimal weighting matrix for individual  $i$

$$\Omega_i = \Omega_{0i} + \sum_{j=1}^{\infty} (\Omega_{ji} + \Omega'_{ji}).$$

To facilitate the asymptotic analysis, in the estimation of the optimal weighting matrix we assume that  $g(z_{it}; \theta_0, \alpha_{i0})$  is a martingale difference sequence with respect to the sigma algebra  $\sigma(\alpha_{i0}, z_{i,t-1}, z_{i,t-2}, \dots)$ , so that  $\Omega_i = \Omega_{0i}$  and  $\widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) = \widehat{\Omega}_{0i}(\tilde{\theta}, \tilde{\alpha}_i)$ . This assumption holds in rational expectation models. We do not impose this assumption to derive the limiting distribution of the one-step FE-GMM estimator.

For the subsequent analysis of the asymptotic properties of the estimator, it is convenient to consider the concentrated or profile problem. This problem is a two-step procedure. In the first step the program is solved for the individual effects, given the value of the common parameter  $\theta$ . The First Order Conditions (FOC) for this stage, reparametrized conveniently as in Newey and Smith (2004), are the following

$$\widehat{t}_i(\theta, \widehat{\gamma}_i(\theta)) = - \begin{pmatrix} \widehat{G}_{\alpha_i}(\theta, \widehat{\alpha}_i(\theta))' \widehat{\lambda}_i(\theta) \\ \widehat{g}_i(\theta, \widehat{\alpha}_i(\theta)) + \widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) \widehat{\lambda}_i(\theta) \end{pmatrix} = 0, \quad (i = 1, \dots, n),$$

where  $\lambda_i$  is a  $d_g$ -vector of individual Lagrange multipliers for the moment conditions, and  $\gamma_i := (\alpha'_i, \lambda'_i)'$  is an extended  $(d_\alpha + d_g)$ -vector of individual effects. Then, the solutions to the previous equations are plugged into the original problem, leading to the following first order conditions for  $\theta$ ,  $\widehat{s}(\widehat{\theta}) = 0$ , where

$$\widehat{s}(\theta) = n^{-1} \sum_{i=1}^n \widehat{s}_i(\theta, \widehat{\gamma}_i(\theta)) = -n^{-1} \sum_{i=1}^n \widehat{G}_{\theta_i}(\theta, \widehat{\alpha}_i(\theta))' \widehat{\lambda}_i(\theta),$$

is the profile score function for  $\theta$ .<sup>7</sup>

Fixed effects estimators of smooth functions of parameters and observations are constructed using the plug-in principle, i.e.  $\hat{\zeta} = \hat{\zeta}(\hat{\theta})$  where

$$\hat{\zeta}(\theta) = (nT)^{-1} \sum_{i=1}^n \sum_{t=1}^T \zeta(z_{it}; \theta, \hat{\alpha}_i(\theta)).$$

Similarly, moments of the individual effects are estimated by  $\hat{\mu} = \hat{\mu}(\hat{\theta})$ , where

$$\hat{\mu}(\theta) = n^{-1} \sum_{i=1}^n \mu(\hat{\alpha}_i(\theta)).$$

#### 4. ASYMPTOTIC THEORY FOR FE-GMM ESTIMATORS

In this section we analyze the properties of one-step and two-step FE-GMM estimators in large samples. We show consistency and derive the asymptotic distributions for estimators of individual effects, common parameters and other quantities of interest under sequences where both  $n$  and  $T$  pass to infinity with the sample size. We establish results separately for one-step and two-step estimators because the former are derived under less restrictive assumptions.

We make the following assumptions to show uniform consistency of the FE-GMM one-step estimator:

**Condition 1** (Sampling and asymptotics). (i) For each  $i$ ,  $z_i := \{z_{it} : 1 \leq t \leq T\}$  is a stationary mixing sequence of random vectors with strong mixing coefficients  $a_i(l) = \sup_t \sup_{A \in \mathcal{A}_t^i, D \in \mathcal{D}_{t+l}^i} |P(A \cap D) - P(A)P(D)|$ , where  $\mathcal{A}_t^i = \sigma(\alpha_{i0}, z_{it}, z_{i,t-1}, \dots)$  and  $\mathcal{D}_t^i = \sigma(\alpha_{i0}, z_{it}, z_{i,t+1}, \dots)$ , such that  $\sup_i |a_i(l)| \leq Ca^l$  for some  $0 < a < 1$  and some  $C > 0$ ; (ii)  $\{z_i : 1 \leq i \leq n\}$  are independent across  $i$ ; (iii)  $n, T \rightarrow \infty$  such that  $n/T \rightarrow \kappa^2$ , where  $0 < \kappa^2 < \infty$ ; and (iv)  $\dim[g(\cdot; \theta, \alpha_i)] = d_g < \infty$ .

For a matrix or vector  $A$ , let  $|A|$  denote the Euclidean norm, that is  $|A|^2 = \text{trace}[AA']$ .

**Condition 2** (Regularity and identification). (i) The vector of moment functions  $g(\cdot; \theta, \alpha) = (g_1(\cdot; \theta, \alpha), \dots, g_{d_g}(\cdot; \theta, \alpha))'$  is continuous in  $(\theta, \alpha) \in \Upsilon$ ; (ii) the parameter space  $\Upsilon$  is a compact, convex subset of  $\mathbb{R}^{d_\theta + d_\alpha}$ ; (iii)  $\dim(\theta, \alpha) = d_\theta + d_\alpha \leq d_g$ ; (iv) there exists a function  $M(z_{it})$  such that  $|g_k(z_{it}; \theta, \alpha_i)| \leq M(z_{it})$ ,  $|\partial g_k(z_{it}; \theta, \alpha_i) / \partial(\theta, \alpha_i)| \leq M(z_{it})$ , for

<sup>7</sup>In the original parametrization, the FOC can be written as

$$n^{-1} \sum_{i=1}^n \hat{G}_{\theta_i}(\hat{\theta}, \hat{\alpha}_i(\hat{\theta}))' \hat{\Omega}_i(\hat{\theta}, \hat{\alpha}_i)^- \hat{g}_i(\hat{\theta}, \hat{\alpha}_i(\hat{\theta})) = 0,$$

where the superscript  $-$  denotes a generalized inverse.

$k = 1, \dots, d_g$ , and  $\sup_i E \left[ M(z_{it})^{4+\delta} \right] < \infty$  for some  $\delta > 0$ ; and (v) there exists a deterministic sequence of symmetric finite positive definite matrices  $\{W_i : 1 \leq i \leq n\}$  such that  $\sup_{1 \leq i \leq n} |\widehat{W}_i - W_i| \rightarrow_P 0$ , and, for each  $\eta > 0$

$$\inf_i \left[ Q_i^W(\theta_0, \alpha_{i0}) - \sup_{\{(\theta, \alpha) : |(\theta, \alpha) - (\theta_0, \alpha_{i0})| > \eta\}} Q_i^W(\theta, \alpha) \right] > 0,$$

where

$$Q_i^W(\theta, \alpha_i) := -g_i(\theta, \alpha_i)' W_i^{-1} g_i(\theta, \alpha_i), \quad g_i(\theta, \alpha_i) := E[\widehat{g}_i(\theta, \alpha_i)].$$

Conditions 1(i)-(ii) impose cross sectional independence, but allow for weak time series dependence as in Hahn and Kuersteiner (2011). Conditions 1(iii)-(iv) describe the asymptotic sequences that we consider where  $T$  and  $n$  grow at the same rate with the sample size, whereas the number of moments  $d_g$  is fixed. Condition 2 adapts standard assumptions of the GMM literature to guarantee the identification of the parameters based on time series variation for all the individuals, see Newey and McFadden (1994). The dominance and moment conditions in 2(iv) are used to establish uniform consistency of the estimators of the individual effects.

**Theorem 1** (Uniform consistency of one-step estimators). *Suppose that Conditions 1 and 2 hold. Then, for any  $\eta > 0$*

$$\Pr \left( \left| \tilde{\theta} - \theta_0 \right| \geq \eta \right) = o(T^{-1}),$$

where  $\tilde{\theta} = \arg \max_{\{(\theta, \alpha_i) \in \Upsilon\}_{i=1}^n} \frac{1}{n} \sum_{i=1}^n \widehat{Q}_i^W(\theta, \alpha_i)$  and  $\widehat{Q}_i^W(\theta, \alpha_i) := -\widehat{g}_i(\theta, \alpha_i)' \widehat{W}_i^{-1} \widehat{g}_i(\theta, \alpha_i)$ . Also, for any  $\eta > 0$

$$\Pr \left( \sup_{1 \leq i \leq n} |\tilde{\alpha}_i - \alpha_{i0}| \geq \eta \right) = o(T^{-1}),$$

where  $\tilde{\alpha}_i = \arg \max_{\alpha} \widehat{Q}_i^W(\tilde{\theta}, \alpha)$ , and  $\Pr \left\{ \sup_{1 \leq i \leq n} |\tilde{\lambda}_i| \geq \eta \right\} = o(T^{-1})$ , where  $\tilde{\lambda}_i = -\widehat{W}_i^{-1} \widehat{g}_i(\tilde{\theta}, \tilde{\alpha}_i)$ .

Let  $\Sigma_{\alpha_i}^W := (G'_{\alpha_i} W_i^{-1} G_{\alpha_i})^{-1}$ ,  $H_{\alpha_i}^W := \Sigma_{\alpha_i}^W G'_{\alpha_i} W_i^{-1}$ ,  $P_{\alpha_i}^W := W_i^{-1} - W_i^{-1} G_{\alpha_i} H_{\alpha_i}^W$ ,  $J_{si}^W := G'_{\theta_i} P_{\alpha_i}^W G_{\theta_i}$  and  $J_s^W := \bar{E}[J_{si}^W]$ . We use the following additional assumptions to derive the limiting distribution of the one-step estimator:

**Condition 3** (Regularity). (i) For each  $i$ ,  $(\theta_0, \alpha_{i0}) \in \text{int}[\Upsilon]$ ; and (ii)  $J_s^W$  is finite positive definite, and  $\{G'_{\alpha_i} W_i^{-1} G_{\alpha_i} : 1 \leq i \leq n\}$  is a sequence of finite positive definite matrices, where  $\{W_i : 1 \leq i \leq n\}$  is the sequence of matrices of Condition 2(v).

**Condition 4** (Smoothness). (i) There exists a function  $M(z_{it})$  such that, for  $k = 1, \dots, d_g$ ,

$$|\partial^{d_1+d_2} g_k(z_{it}; \theta, \alpha_i) / \partial \theta^{d_1} \partial \alpha_i^{d_2}| \leq M(z_{it}), \quad 0 \leq d_1 + d_2 \leq 1, \dots, 5,$$

and  $\sup_i E \left[ M(z_{it})^{5(d_\theta + d_\alpha + 6)/(1-10v) + \delta} \right] < \infty$ , for some  $\delta > 0$  and  $0 < v < 1/10$ ; and (ii) there exists  $\xi_i(z_{it})$  such that  $\widehat{W}_i = W_i + \sum_{t=1}^T \xi_i(z_{it})/T + R_i^W/T$ , where  $\max_i |R_i^W| = o_P(T^{1/2})$ ,  $E[\xi_i(z_{it})] = 0$ , and  $\sup_i E[|\xi_i(z_{it})|^{20/(1-10v) + \delta}] < \infty$ , for some  $\delta > 0$  and  $0 < v < 1/10$ .

Condition 3 is the panel data analog to the standard asymptotic normality condition for GMM with cross sectional data, see Newey and McFadden (1994). Condition 4 is similar to Condition 4 in Hahn and Kuersteiner (2011), and guarantees the existence of higher order expansions for the GMM estimators and the uniform convergence of their remainder terms.

Let  $G_{\alpha\alpha_i} := (G'_{\alpha\alpha_{i,1}}, \dots, G'_{\alpha\alpha_{i,q}})'$ , where  $G_{\alpha\alpha_{i,j}} = E[\partial G_{\alpha_i}(z_{it})/\partial \alpha_{i,j}]$ , and  $G_{\theta\alpha_i} := (G'_{\theta\alpha_{i,1}}, \dots, G'_{\theta\alpha_{i,q}})'$ , where  $G_{\theta\alpha_{i,j}} = E[\partial G_{\theta_i}(z_{it})/\partial \alpha_{i,j}]$ . The symbol  $\otimes$  denotes kronecker product of matrices,  $I_{d_\alpha}$  a  $d_\alpha \times d_\alpha$  identity matrix,  $e_j$  a unitary  $d_g$ -vector with 1 in row  $j$ , and  $P_{\alpha_i,j}^W$  the  $j$ -th column of  $P_{\alpha_i}^W$ . Recall that the extended individual effect is  $\gamma_i = (\alpha'_i, \lambda'_i)'$ .

**Lemma 1** (Asymptotic expansion for one-step estimators of individual effects). *Under Conditions 1, 2, 3, and 4,*

$$(4.1) \quad \sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}) = \tilde{\psi}_i^W + T^{-1/2}Q_{1i}^W + T^{-1}R_{2i}^W,$$

where  $\tilde{\gamma}_{i0} := \tilde{\gamma}_i(\theta_0)$ ,

$$\tilde{\psi}_i^W = - \begin{pmatrix} H_{\alpha_i}^W \\ P_{\alpha_i}^W \end{pmatrix} T^{-1/2} \sum_{t=1}^T g(z_{it}) \xrightarrow{d} N(0, V_i^W),$$

$n^{-1/2} \sum_{i=1}^n \tilde{\psi}_i^W \xrightarrow{d} N(0, \bar{E}[V_i^W])$ ,  $n^{-1} \sum_{i=1}^n Q_{1i}^W \xrightarrow{p} \bar{E}[B_{\gamma_i}^W]$ ,  $B_{\gamma_i}^W = B_{\gamma_i}^{W,I} + B_{\gamma_i}^{W,G} + B_{\gamma_i}^{W,1S}$ ,  $\sup_{1 \leq i \leq n} R_{2i}^W = o_P(\sqrt{T})$ , for

$$\begin{aligned} V_i^W &= \begin{pmatrix} H_{\alpha_i}^W \\ P_{\alpha_i}^W \end{pmatrix} \Omega_i(H_{\alpha_i}^{W'}, P_{\alpha_i}^W), \\ B_{\gamma_i}^{W,I} &= \begin{pmatrix} B_{\alpha_i}^{W,I} \\ B_{\lambda_i}^{W,I} \end{pmatrix} = \begin{pmatrix} H_{\alpha_i}^W \\ P_{\alpha_i}^W \end{pmatrix} \left( \sum_{j=-\infty}^{\infty} E[G_{\alpha_i}(z_{it}) H_{\alpha_i}^W g(z_{i,t-j})] - \sum_{j=1}^{d_\alpha} G_{\alpha\alpha_{i,j}} H_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} / 2 \right), \\ B_{\gamma_i}^{W,G} &= \begin{pmatrix} B_{\alpha_i}^{W,G} \\ B_{\lambda_i}^{W,G} \end{pmatrix} = \begin{pmatrix} -\Sigma_{\alpha_i}^W \\ H_{\alpha_i}^{W'} \end{pmatrix} \sum_{j=-\infty}^{\infty} E[G_{\alpha_i}(z_{it})' P_{\alpha_i}^W g(z_{i,t-j})], \\ B_{\gamma_i}^{W,1S} &= \begin{pmatrix} B_{\alpha_i}^{W,1S} \\ B_{\lambda_i}^{W,1S} \end{pmatrix} = \begin{pmatrix} \Sigma_{\alpha_i}^W \\ -H_{\alpha_i}^{W'} \end{pmatrix} \left( \sum_{j=1}^{d_\alpha} G'_{\alpha\alpha_{i,j}} P_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} / 2 + \sum_{j=1}^{d_g} G'_{\alpha\alpha_i}(I_{d_\alpha} \otimes e_j) H_{\alpha_i}^W \Omega_i P_{\alpha_i,j}^W / 2 \right) \\ &\quad + \begin{pmatrix} H_{\alpha_i}^W \\ P_{\alpha_i}^W \end{pmatrix} \sum_{j=-\infty}^{\infty} E[\xi_i(z_{it}) P_{\alpha_i}^W g(z_{i,t-j})]. \end{aligned}$$

**Theorem 2** (Limit distribution of one-step estimators of common parameters). *Under Conditions 1, 2, 3 and 4,*

$$\sqrt{nT}(\tilde{\theta} - \theta_0) \xrightarrow{d} -(J_s^W)^{-1} N(\kappa B_s^W, V_s^W),$$

where

$$J_s^W = \bar{E} [G'_{\theta_i} P_{\alpha_i}^W G_{\theta_i}], V_s^W = \bar{E} [G'_{\theta_i} P_{\alpha_i}^W \Omega_i P_{\alpha_i}^W G_{\theta_i}], B_s^W = \bar{E} [B_{si}^{W,B} + B_{si}^{W,C} + B_{si}^{W,V}],$$

and

$$\begin{aligned} B_{si}^{W,B} &= -G'_{\theta_i} (B_{\lambda_i}^{W,I} + B_{\lambda_i}^{W,G} + B_{\lambda_i}^{W,1S}), B_{si}^{W,C} = \sum_{j=-\infty}^{\infty} E[G_{\theta_i}(z_{it})' P_{\alpha_i}^W g_i(z_{i,t-j})], \\ B_{si}^{W,V} &= -\sum_{j=1}^{d_\alpha} G'_{\theta_{\alpha_i,j}} P_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} / 2 - \sum_{j=1}^{d_g} G'_{\theta_{\alpha_i}} (I_{d_\alpha} \otimes e_j) H_{\alpha_i}^W \Omega_i P_{\alpha_i,j} / 2. \end{aligned}$$

The expressions for  $B_{\lambda_i}^{W,I}$ ,  $B_{\lambda_i}^{W,G}$ , and  $B_{\lambda_i}^{W,1S}$  are given in Lemma 1.

The source of the bias is the non-zero expectation of the profile score of  $\theta$  at the true parameter value, due to the substitution of the unobserved individual effects by sample estimators. These estimators converge to their true parameter value at a rate  $\sqrt{T}$ , which is slower than  $\sqrt{nT}$ , the rate of convergence of the estimator of the common parameter, under asymptotic sequences where  $n$  and  $T$  grow with the sample size. Intuitively, only observations for each individual convey information about the corresponding individual effect. In nonlinear and dynamic models, the slow convergence of the estimator of the individual effect introduces bias in the estimators of the rest of parameters. The expression of this bias can be explained with an expansion of the score around the true value of the individual effects<sup>8</sup>

$$\begin{aligned} E[\hat{s}_i^W(\theta_0, \tilde{\gamma}_{i0})] &= E[\hat{s}_i^W] + E[\hat{s}_{\gamma_i}^W]' E[\tilde{\gamma}_{i0} - \gamma_{i0}] + E[(\hat{s}_{\gamma_i}^W - E[\hat{s}_{\gamma_i}^W])'(\tilde{\gamma}_{i0} - \gamma_{i0})] \\ &+ E\left[\sum_{j=1}^{d_\alpha+d_g} (\tilde{\gamma}_{i0,j} - \gamma_{i0,j}) E[\hat{s}_{\gamma_{\gamma i}}^W] (\tilde{\gamma}_{i0} - \gamma_{i0})\right] / 2 + o(T^{-1}) \\ &= 0 + B_s^{W,B}/T + B_s^{W,C}/T + B_s^{W,V}/T + o(T^{-1}). \end{aligned}$$

This expression shows that the bias has the same three components as in the MLE case, see Hahn and Newey (2004). The first component,  $B_s^{W,B}$ , comes from the higher-order bias of the estimator of the individual effects. The second component,  $B_s^{W,C}$ , is a correlation term and is present because individual effects and common parameters are estimated using the same observations. The third component,  $B_s^{W,V}$ , is a variance term. The bias of the individual effects,  $B_s^{W,B}$ , can be further decomposed in three terms corresponding to the asymptotic bias for a GMM estimator with the optimal score,  $B_{\lambda}^{W,I}$ , when  $W$  is used as the weighting

<sup>8</sup>Using the notation introduced in Section 3, the score is

$$\hat{s}^W(\theta_0) = n^{-1} \sum_{i=1}^n \hat{s}_i^W(\theta_0, \tilde{\gamma}_{i0}) = -n^{-1} \sum_{i=1}^n \hat{G}_{\theta_i}(\theta_0, \tilde{\alpha}_{i0})' \tilde{\lambda}_{i0},$$

where  $\tilde{\gamma}_{i0} = (\tilde{\alpha}'_{i0}, \tilde{\lambda}'_{i0})$  is the solution to

$$\hat{t}_i^W(\theta_0, \tilde{\gamma}_{i0}) = - \begin{pmatrix} \hat{G}_{\alpha_i}(\theta_0, \tilde{\alpha}_{i0})' \tilde{\lambda}_{i0} \\ \hat{g}_i(\theta_0, \tilde{\alpha}_{i0}) + W_i \tilde{\lambda}_{i0} \end{pmatrix} = 0.$$

function; the bias arising from estimation of  $G_{\alpha_i}$ ,  $B_{\lambda}^{W,G}$ ; and the bias arising from not using an optimal weighting matrix,  $B_{\lambda}^{W,1S}$ .

We use the following condition to show the consistency of the two-step FE-GMM estimator:

**Condition 5** (Smoothness, regularity, and martingale). *(i) There exists a function  $M(z_{it})$  such that  $|g_k(z_{it}; \theta, \alpha_i)| \leq M(z_{it})$ ,  $|\partial g_k(z_{it}; \theta, \alpha_i) / \partial(\theta, \alpha_i)| \leq M(z_{it})$ , for  $k = 1, \dots, d_g$ , and  $\sup_i E \left[ M(z_{it})^{10(d_\theta + d_\alpha + 6)/(1-10v) + \delta} \right] < \infty$ , for some  $\delta > 0$  and  $0 < v < 1/10$ ; (ii)  $\{\Omega_i : 1 \leq i \leq n\}$  is a sequence of finite positive definite matrices; and (iii) for each  $i$ ,  $g(z_{it}; \theta_0, \alpha_{i0})$  is a martingale difference sequence with respect to  $\sigma(\alpha_{i0}, z_{i,t-1}, z_{i,t-2}, \dots)$ .*

Conditions 5(i)-(ii) are used to establish the uniform consistency of the estimators of the individual weighting matrices. Condition 5(iii) is convenient to simplify the expressions of the optimal weighting matrices. It holds, for example, in rational expectation models that commonly arise in economic applications.

**Theorem 3** (Uniform consistency of two-step estimators). *Suppose that Conditions 1, 2, 3 and 5 hold. Then, for any  $\eta > 0$*

$$\Pr \left( \left| \hat{\theta} - \theta_0 \right| \geq \eta \right) = o(T^{-1}),$$

where  $\hat{\theta} = \arg \max_{\{(\theta', \alpha'_i)\}_{i=1}^n \in \Upsilon} \sum_{i=1}^n \hat{Q}_i^\Omega(\theta, \alpha_i)$  and  $\hat{Q}_i^\Omega(\theta, \alpha_i) := -\hat{g}_i(\theta, \alpha_i)' \hat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i)^{-1} \hat{g}_i(\theta, \alpha_i)$ . Also, for any  $\eta > 0$

$$\Pr \left( \sup_{1 \leq i \leq n} |\hat{\alpha}_i - \alpha_0| \geq \eta \right) = o(T^{-1}),$$

where  $\hat{\alpha}_i = \arg \max_{\alpha} \hat{Q}_i^\Omega(\hat{\theta}, \alpha)$ , and  $\Pr \left( \sup_{1 \leq i \leq n} |\hat{\lambda}_i| \geq \eta \right) = o(T^{-1})$ , where  $\hat{g}_i(\hat{\theta}, \hat{\alpha}_i) + \hat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) \hat{\lambda}_i = 0$ .

We replace Condition 4 by the following condition to obtain the limit distribution of the two-step estimator:

**Condition 6** (Smoothness). *There exists some  $M(z_{it})$  such that, for  $k = 1, \dots, d_g$*

$$|\partial^{d_1+d_2} g_k(z_{it}; \theta, \alpha_i) / \partial \theta^{d_1} \partial \alpha_i^{d_2}| \leq M(z_{it}) \quad 0 \leq d_1 + d_2 \leq 1, \dots, 5,$$

and  $\sup_i E \left[ M(z_{it})^{10(d_\theta + d_\alpha + 6)/(1-10v) + \delta} \right] < \infty$ , for some  $\delta > 0$  and  $0 < v < 1/10$ .

Condition 6 guarantees the existence of higher order expansions for the estimators of the weighting matrices and uniform convergence of their remainder terms. Conditions 5 and 6 are stronger versions of conditions 2(iv), 2(v) and 4. They are presented separately because they are only needed when there is a first stage where the weighting matrices are estimated.

Let  $\Sigma_{\alpha_i} := (G'_{\alpha_i} \Omega_i^{-1} G_{\alpha_i})^{-1}$ ,  $H_{\alpha_i} := \Sigma_{\alpha_i} G'_{\alpha_i} \Omega_i^{-1}$ , and  $P_{\alpha_i} := \Omega_i^{-1} - \Omega_i^{-1} G_{\alpha_i} H_{\alpha_i}$ .

**Lemma 2** (Asymptotic expansion for two-step estimators of individual effects). *Under the Conditions 1, 2, 3, 4, and 5,*

$$(4.2) \quad \sqrt{T}(\hat{\gamma}_{i0} - \gamma_{i0}) = \tilde{\psi}_i + T^{-1/2}B_{\gamma_i} + T^{-1}R_{2i},$$

where  $\hat{\gamma}_{i0} := \hat{\gamma}_i(\theta_0)$ ,

$$\tilde{\psi}_i = - \begin{pmatrix} H_{\alpha_i} \\ P_{\alpha_i} \end{pmatrix} T^{-1/2} \sum_{t=1}^T g(z_{it}) \xrightarrow{d} N(0, V_i),$$

$n^{-1/2} \sum_{i=1}^n \tilde{\psi}_i \xrightarrow{d} N(0, \bar{E}[V_i])$ ,  $B_{\gamma_i} = B_{\gamma_i}^I + B_{\gamma_i}^G + B_{\gamma_i}^\Omega + B_{\gamma_i}^W$ ,  $\sup_{1 \leq i \leq n} R_{2i} = o_P(\sqrt{T})$ , with, for

$$\begin{aligned} V_i &= \text{diag}(\Sigma_{\alpha_i}, P_{\alpha_i}), \\ B_{\gamma_i}^I &= \begin{pmatrix} B_{\alpha_i}^I \\ B_{\lambda_i}^I \end{pmatrix} = \begin{pmatrix} H_{\alpha_i} \\ P_{\alpha_i} \end{pmatrix} \left( - \sum_{j=1}^{d_\alpha} G_{\alpha\alpha_i,j} \Sigma_{\alpha_i} / 2 + E[G_{\alpha_i}(z_{it}) H_{\alpha_i} g(z_{i,t-j})] \right), \\ B_{\gamma_i}^G &= \begin{pmatrix} B_{\alpha_i}^G \\ B_{\lambda_i}^G \end{pmatrix} = \begin{pmatrix} -\Sigma_{\alpha_i} \\ H'_{\alpha_i} \end{pmatrix} \sum_{j=0}^{\infty} E[G_{\alpha_i}(z_{it})' P_{\alpha_i} g(z_{i,t-j})], \\ B_{\gamma_i}^\Omega &= \begin{pmatrix} B_{\alpha_i}^\Omega \\ B_{\lambda_i}^\Omega \end{pmatrix} = \begin{pmatrix} H_{\alpha_i} \\ P_{\alpha_i} \end{pmatrix} \sum_{j=0}^{\infty} E[g(z_{it}) g(z_{it})' P_{\alpha_i} g(z_{i,t-j})], \\ B_{\gamma_i}^W &= \begin{pmatrix} B_{\alpha_i}^W \\ B_{\lambda_i}^W \end{pmatrix} = \begin{pmatrix} H_{\alpha_i} \\ P_{\alpha_i} \end{pmatrix} \sum_{j=1}^{d_\alpha} \Omega_{\alpha_i,j} (H_{\alpha_i,j}^{W'} - H'_{\alpha_i,j}). \end{aligned}$$

**Theorem 4** (Limit distribution for two-step estimators of common parameters). *Under the Conditions 1, 2, 3, 4, 5 and 6,*

$$\sqrt{nT}(\hat{\theta} - \theta_0) \xrightarrow{d} -J_s^{-1} N(\kappa B_s, J_s),$$

where  $J_s = \bar{E}[G'_{\theta_i} P_{\alpha_i} G_{\theta_i}]$ ,  $B_s = \bar{E}[B_{si}^B + B_{si}^C]$ ,  $B_{si}^B = -G'_{\theta_i} [B_{\lambda_i}^I + B_{\lambda_i}^G + B_{\lambda_i}^\Omega + B_{\lambda_i}^W]$ ,  $B_{si}^C = \sum_{j=0}^{\infty} E[G_{\theta_i}(z_{it})' P_{\alpha_i} g(z_{i,t-j})]$ . The expressions for  $B_{\lambda_i}^I$ ,  $B_{\lambda_i}^G$ ,  $B_{\lambda_i}^\Omega$  and  $B_{\lambda_i}^W$  are given in Lemma 2.

Theorem 4 establishes that one iteration of the GMM procedure not only improves asymptotic efficiency by reducing the variance of the influence function, but also removes the variance and non-optimal weighting matrices components from the bias. The higher-order bias of the estimator of the individual effects,  $B_\lambda^B$ , now has four components, as in Newey and Smith (2004). These components correspond to the asymptotic bias for a GMM estimator with the optimal score,  $B_\lambda^I$ ; the bias arising from estimation of  $G_{\alpha_i}$ ,  $B_\lambda^G$ ; the bias arising from estimation of  $\Omega_i$ ,  $B_\lambda^\Omega$ ; and the bias arising from the choice of the preliminary first step estimator,  $B_\lambda^W$ . An additional iteration of the GMM estimator removes the term  $B_\lambda^W$ .

The general procedure for deriving the asymptotic distribution of the FE-GMM estimators consists of several expansions. First, we derive higher-order asymptotic expansions for the



estimators of the individual effects, with the common parameter fixed at its true value  $\theta_0$ . Next, we obtain the asymptotic distribution for the profile score of the common parameter at  $\theta_0$  using the expansions of the estimators of the individual effects. Finally, we derive the asymptotic distribution of estimator for the common parameter multiplying the asymptotic distribution of the score by the limit profile Jacobian matrix. This procedure is detailed in the online appendix Fernández-Val and Lee (2012). Here we characterize the asymptotic bias in a linear correlated random coefficient model with endogenous regressors. Motivated by the numerical and empirical examples that follow, we consider a model where only the variables with common parameter are endogenous and allow for the moment conditions not to be martingale difference sequences.

**Example: Correlated random coefficient model with endogenous regressors.** We consider a simplified version of the models in the empirical and numerical examples. The notation is the same as in the theorems discussed above. The moment condition is

$$g(z_{it}; \theta, \alpha_i) = w_{it}(y_{it} - x'_{1it}\alpha_i - x'_{2it}\theta),$$

where  $w_{it} = (x'_{1it}, w'_{2it})'$  and  $z_{it} = (x'_{1it}, x'_{2it}, w'_{2it}, y_{it})'$ . That is, only the regressors with common coefficients are endogenous. Let  $\epsilon_{it} = y_{it} - x'_{1it}\alpha_{i0} - x'_{2it}\theta_0$ . To simplify the expressions for the bias, we assume that  $\epsilon_{it} \mid w_i, \alpha_i \sim i.i.d.(0, \sigma_\epsilon^2)$  and  $E[x_{2it}\epsilon_{i,t-j} \mid w_i, \alpha_i] = E[x_{2it}\epsilon_{i,t-j}]$ , for  $w_i = (w_{i1}, \dots, w_{iT})'$  and  $j \in \{0, \pm 1, \dots\}$ . Under these conditions, the optimal weighted matrices are proportional to  $E[w_{it}w'_{it}]$ , which do not depend on  $\theta_0$  and  $\alpha_{i0}$ . We can therefore obtain the optimal GMM estimator in one step using the sample averages  $T^{-1} \sum_{t=1}^T w_{it}w'_{it}$  to estimate the optimal weighting matrices.

In this model, it is straightforward to see that the estimators of the individual effects have no bias, that is  $B_{\gamma_i}^{W,I} = B_{\gamma_i}^{W,G} = B_{\gamma_i}^{W,1S} = 0$ . By linearity of the first order conditions in  $\theta$  and  $\alpha_i$ ,  $B_{si}^{W,V} = 0$ . The only source of bias is the correlation between the estimators of  $\theta$  and  $\alpha_i$ . After some straightforward but tedious algebra, this bias simplifies to

$$B_{si}^{W,C} = -(d_g - d_\alpha) \sum_{j=-\infty}^{\infty} E[x_{2it}\epsilon_{i,t-j}].$$

For the limit Jacobian, we find

$$J_s^W = \bar{E} \left\{ E[\tilde{x}_{2it}\tilde{w}'_{2it}] E[\tilde{w}_{2it}\tilde{w}'_{2it}]^{-1} E[\tilde{w}_{2it}\tilde{x}'_{2it}] \right\},$$

where variables with tilde indicate residuals of population linear projections of the corresponding variable on  $x_{1it}$ , for example  $\tilde{x}_{2it} = x_{2it} - E[x_{2it}x'_{1it}]E[x_{1it}x'_{1it}]^{-1}x_{1it}$ . The expression of the bias is

$$(4.3) \quad \mathcal{B}(\theta_0) = -(d_g - d_\alpha)(J_s^W)^{-1} \bar{E} \sum_{j=-\infty}^{\infty} E[\tilde{x}_{2it}(\tilde{y}_{i,t-j} - \tilde{x}'_{2i,t-j}\theta_0)].$$

In random coefficient models the ultimate quantities of interest are often functions of the data, model parameters and individual effects. The following corollaries characterize the asymptotic distributions of the fixed effects estimators of these quantities. The first corollary applies to averages of functions of the data and individual effects such as average partial effects and average derivatives in nonlinear models, and average elasticities in linear models with variables in levels. Section 6 gives an example of these elasticities. The second corollary applies to averages of smooth functions of the individual effects including means, variances and other moments of the distribution of these effects. Sections 2 and 6 give examples of these functions. We state the results only for estimators constructed from two-step estimators of the common parameters and individual effects. Similar results apply to estimators constructed from one-step estimators. Both corollaries follow from Lemma 2 and Theorem 4 by the delta method.

**Corollary 1** (Asymptotic distribution for fixed effects averages). *Let  $\zeta(z; \theta, \alpha_i)$  be a twice continuously differentiable function in its second and third argument, such that  $\inf_i \text{Var}[\zeta(z_{it})] > 0$ ,  $\bar{E}E[\zeta(z_{it})^2] < \infty$ ,  $\bar{E}E|\zeta_\alpha(z_{it})|^2 < \infty$ , and  $\bar{E}E|\zeta_\theta(z_{it})|^2 < \infty$ , where the subscripts on  $\zeta$  denote partial derivatives. Then, under the conditions of Theorem 4*

$$\sqrt{nT}(\hat{\zeta} - \zeta) \xrightarrow{d} N(\kappa B_\zeta, V_\zeta),$$

where  $\zeta = \bar{E}E[\zeta(z_{it})]$ ,

$$B_\zeta = \bar{E}E \left[ - \sum_{j=0}^{\infty} \zeta_{\alpha_i}(z_{it})' H_{\alpha_i} g(z_{i,t-j}) + \zeta_{\alpha_i}(z_{it})' B_{\alpha_i} + \sum_{j=1}^{d_\alpha} \zeta_{\alpha\alpha_{i,j}}(z_{it})' \Sigma_{\alpha_i} / 2 - \zeta_\beta(z_{it})' J_s^{-1} B_s \right],$$

for  $B_{\alpha_i} = B_{\alpha_i}^I + B_{\alpha_i}^G + B_{\alpha_i}^\Omega + B_{\alpha_i}^W$ , and

$$V_\zeta = \bar{E}E \left[ \zeta_{\alpha_i}(z_{it})' \Sigma_{\alpha_i} \zeta_{\alpha_i}(z_{it}) + \zeta_\theta(z_{it})' J_s^{-1} \zeta_\theta(z_{it}) + \sum_{j=-\infty}^{\infty} (\zeta(z_{it}) - \zeta)(\zeta(z_{i,t-j}) - \zeta) \right].$$

**Corollary 2** (Asymptotic distribution for smooth functions of individual effects). *Let  $\mu(\alpha_i)$  be a twice differentiable function such that  $\bar{E}[\mu(\alpha_{i0})^2] < \infty$  and  $\bar{E}|\mu_\alpha(\alpha_{i0})|^2 < \infty$ , where the subscripts on  $\mu$  denote partial derivatives. Then, under the conditions of Theorem 4*

$$\sqrt{n}(\hat{\mu} - \mu) \xrightarrow{d} N(\kappa B_\mu, V_\mu),$$

where  $\mu = \bar{E}[\mu(\alpha_{i0})]$ ,

$$B_\mu = \bar{E} \left[ \mu_{\alpha_i}(\alpha_{i0})' B_{\alpha_i} + \sum_{j=1}^{d_\alpha} \mu_{\alpha\alpha_{i,j}}(\alpha_{i0})' \Sigma_{\alpha_i} / 2 \right],$$

for  $B_{\alpha_i} = B_{\alpha_i}^I + B_{\alpha_i}^G + B_{\alpha_i}^\Omega + B_{\alpha_i}^W$ , and  $V_\mu = \bar{E}[(\mu(\alpha_{i0}) - \mu)^2]$ .

The convergence rates are different in Corollaries 1 and 2. The  $(nT)^{-1/2}$  rate in Corollary 1 follows because the averages are over the cross sectional and time dimensions; whereas the  $n^{-1/2}$  rate in Corollary 2 follows because the averages are only over the cross sectional dimension.

## 5. BIAS CORRECTIONS

The FE-GMM estimators of common parameters, while consistent, have bias in the asymptotic distributions under sequences where  $n$  and  $T$  grow at the same rate. These sequences provide a good approximation to the finite sample behavior of the estimators in empirical applications where the time dimension is moderately large. The presence of bias invalidates any asymptotic inference because the bias is of the same order as the variance. In this section we describe bias correction methods to adjust the asymptotic distribution of the FE-GMM estimators of the common parameter and smooth functions of the data, model parameters and individual effects. All the corrections considered are analytical. Alternative corrections based on variations of Jackknife can be implemented using the approaches described in Hahn and Newey (2004) and Dhaene and Jochmans (2010).<sup>9</sup>

We consider three analytical methods that differ in whether the bias is corrected from the estimator or from the first order conditions, and in whether the correction is one-step or iterated for methods that correct the bias from the estimator. All these methods reduce the order of the asymptotic bias without increasing the asymptotic variance. They are based on analytical estimators of the bias of the profile score  $B_s$  and the profile Jacobian matrix  $J_s$ . Since these quantities include cross sectional and time series means  $\bar{E}$  and  $E$  evaluated at the true parameter values for the common parameter and individual effects, they are estimated by the corresponding cross sectional and time series averages evaluated at the FE-GMM estimates. Thus, for any function of the data, common parameter and individual effects  $f_{it}(\theta, \alpha_i)$ , let  $\hat{f}_{it}(\theta) = f_{it}(\theta, \hat{\alpha}_i(\theta))$ ,  $\hat{f}_i(\theta) = \hat{E}[\hat{f}_{it}(\theta)] = T^{-1} \sum_{t=1}^T \hat{f}_{it}(\theta)$  and  $\hat{f}(\theta) = \hat{E}[\hat{f}_i(\theta)] = n^{-1} \sum_{i=1}^n \hat{f}_i(\theta)$ . Next, define  $\hat{\Sigma}_{\alpha_i}(\theta) = [\hat{G}_{\alpha_i}(\theta)' \hat{\Omega}_i^{-1} \hat{G}_{\alpha_i}(\theta)]^{-1}$ ,  $\hat{H}_{\alpha_i}(\theta) = \hat{\Sigma}_{\alpha_i}(\theta) \hat{G}_{\alpha_i}(\theta)' \hat{\Omega}_i^{-1}$ , and  $\hat{P}_{\alpha_i}(\theta) = \hat{\Omega}_i^{-1} \hat{G}_{\alpha_i}(\theta) \hat{H}_{\alpha_i}(\theta)$ . To simplify the presentation, we only give explicit formulas for FE-GMM three-step estimators in the main text. We give the expressions for one and two-step estimators in the Supplementary Appendix. Let

$$\hat{B}(\theta) = -\hat{J}_s(\theta)^{-1} \hat{B}_s(\theta), \quad \hat{B}_s(\theta) = \hat{E}[\hat{B}_{si}^B(\theta) + \hat{B}_{si}^C(\theta)], \quad \hat{J}_s(\theta) = \hat{E}[\hat{G}_{\theta_i}(\theta)' \hat{P}_{\alpha_i}(\theta) \hat{G}_{\theta_i}(\theta)],$$

<sup>9</sup>Hahn, Kuersteiner and Newey (2004) show that analytical, Bootstrap, and Jackknife bias corrections methods are asymptotically equivalent up to third order for MLE. We conjecture that the same result applies to GMM estimators, but the proof is beyond the scope of this paper.

where  $\widehat{B}_{si}^B(\theta) = -\widehat{G}_{\theta_i}(\theta)'[\widehat{B}_{\lambda_i}^I(\theta) + \widehat{B}_{\lambda_i}^G(\theta) + \widehat{B}_{\lambda_i}^\Omega(\theta) + \widehat{B}_{\lambda_i}^W(\theta)]$ ,

$$\widehat{B}_{\lambda_i}^I(\theta) = -\widehat{P}_{\alpha_i}(\theta) \sum_{j=1}^{d_\alpha} \widehat{G}_{\alpha\alpha_{i,j}}(\theta) \widehat{\Sigma}_{\alpha_i}(\theta)/2 + \widehat{P}_{\alpha_i}(\theta) \sum_{j=0}^{\ell} T^{-1} \sum_{t=j+1}^T \widehat{G}_{\alpha_{it}}(\theta) \widehat{H}_{\alpha_i}(\theta) \widehat{g}_{i,t-j}(\theta),$$

$$\widehat{B}_{\lambda_i}^G(\theta) = \widehat{H}_{\alpha_i}(\theta)' \sum_{j=0}^{\infty} T^{-1} \sum_{t=j+1}^T \widehat{G}_{\alpha_{it}}(\theta)' \widehat{P}_{\alpha_i}(\theta) \widehat{g}_{i,t-j}(\theta),$$

$$\widehat{B}_{\lambda_i}^\Omega(\theta) = \widehat{P}_{\alpha_i}(\theta) \sum_{j=0}^{\ell} T^{-1} \sum_{t=j+1}^T \widehat{g}_{it}(\theta) \widehat{g}_{it}(\theta)' \widehat{P}_{\alpha_i}(\theta) \widehat{g}_{i,t-j}(\theta),$$

and  $\widehat{B}_{si}^C(\theta) = T^{-1} \sum_{j=0}^{\ell} \sum_{t=j+1}^T \widehat{G}_{\theta_{it}}(\theta)' \widehat{P}_{\alpha_i}(\theta) \widehat{g}_{i,t-j}(\theta)$ . In the previous expressions, the spectral time series averages that involve an infinite number of terms are trimmed. The trimming parameter  $\ell$  is a positive bandwidth that need to be chosen such that  $\ell \rightarrow \infty$  and  $\ell/T \rightarrow 0$  as  $T \rightarrow \infty$  (Hahn and Kuersteiner, 2011)

The one-step correction of the estimator subtracts an estimator of the expression of the asymptotic bias from the estimator of the common parameter. Using the expressions defined above evaluated at  $\widehat{\theta}$ , the bias-corrected estimator is

$$(5.1) \quad \widehat{\theta}^{BC} = \widehat{\theta} - \widehat{B}(\widehat{\theta})/T.$$

This bias correction is straightforward to implement because it only requires one optimization. The iterated correction is equivalent to solving the nonlinear equation

$$(5.2) \quad \widehat{\theta}^{IBC} = \widehat{\theta} - \widehat{B}(\widehat{\theta}^{IBC})/T.$$

When  $\theta + \widehat{B}(\theta)$  is invertible in  $\theta$ , it is possible to obtain a closed-form solution to the previous equation.<sup>10</sup> Otherwise, an iterative procedure is needed. The score bias-corrected estimator is the solution to the following estimating equation

$$(5.3) \quad \widehat{s}(\widehat{\theta}^{SBC}) - \widehat{B}_s(\widehat{\theta}^{SBC})/T = 0.$$

This procedure, while computationally more intensive, has the attractive feature that both estimator and bias are obtained simultaneously. Hahn and Newey (2004) show that fully iterated bias-corrected estimators solve approximated bias-corrected first order conditions. IBC and SBC are equivalent if the first order conditions are linear in  $\theta$ .

**Example: Correlated random coefficient model with endogenous regressors.** The previous methods can be illustrated in the correlated random coefficient model example in Section 4. Here, the fixed effects GMM estimators have closed forms:

$$\widehat{\alpha}_i(\theta) = \left( \sum_{t=1}^T x_{1it} x'_{1it} \right)^{-1} \sum_{t=1}^T x_{1it} (y_{it} - x'_{2it} \theta),$$

<sup>10</sup>See MacKinnon and Smith (1998) for a comparison of one-step and iterated bias correction methods.

and

$$\hat{\theta} = (\hat{J}_s^W)^{-1} \sum_{i=1}^n \left[ \sum_{t=1}^T \tilde{x}_{2it} \tilde{w}'_{2it} \left( \sum_{t=1}^T \tilde{w}_{2it} \tilde{w}'_{2it} \right)^{-1} \sum_{t=1}^T \tilde{w}_{2it} \tilde{y}_{it} \right],$$

where  $\hat{J}_s^W = \sum_{i=1}^n [\sum_{t=1}^T \tilde{x}_{2it} \tilde{w}'_{2it} (\sum_{t=1}^T \tilde{w}_{2it} \tilde{w}'_{2it})^{-1} \sum_{t=1}^T \tilde{w}_{2it} \tilde{x}'_{2it}]$ , and variables with tilde now indicate residuals of sample linear projections of the corresponding variable on  $x_{1it}$ , for example  $\tilde{x}_{2it} = x_{2it} - \sum_{t=1}^T x_{2it} x'_{1it} (\sum_{t=1}^T x_{1it} x'_{1it})^{-1} x_{1it}$ .

We can estimate the bias of  $\hat{\theta}$  from the analytic formula in expression (4.3) replacing population by sample moments and  $\theta_0$  by  $\hat{\theta}$ , and trimming the number of terms in the spectral expectation,

$$\hat{\mathcal{B}}(\hat{\theta}) = -(d_g - d_\alpha)(\hat{J}_s^W)^{-1} \sum_{i=1}^n \sum_{j=-\ell}^{\ell} \sum_{t=\max(1, j+1)}^{\min(T, T+j)} \tilde{x}_{2it} (\tilde{y}_{i, t-j} - \tilde{x}'_{2i, t-j} \hat{\theta}).$$

The one-step bias corrected estimates of the common parameter  $\theta$  and the average of the individual parameter  $\alpha := E[\alpha_i]$  are

$$\hat{\theta}^{BC} = \hat{\theta} - \hat{\mathcal{B}}(\hat{\theta})/T, \quad \hat{\alpha}^{BC} = n^{-1} \sum_{i=1}^n \hat{\alpha}_i(\hat{\theta}^{BC}).$$

The iterated bias correction estimator can be derived analytically by solving

$$\hat{\theta}^{IBC} = \hat{\theta} - \hat{\mathcal{B}}(\hat{\theta}^{IBC})/T,$$

which has closed-form solution

$$\hat{\theta}^{IBC} = \left[ I_{d_\theta} + (d_g - d_\alpha)(\hat{J}_s^W)^{-1} \sum_{i=1}^n \sum_{j=-\ell}^{\ell} \sum_{t=\max(1, j+1)}^{\min(T, T+j)} \tilde{x}_{2it} \tilde{x}'_{2i, t-j} / (nT^2) \right]^{-1} \times \\ \left[ \hat{\theta} + (d_g - d_\alpha)(\hat{J}_s^W)^{-1} \sum_{i=1}^n \sum_{j=-\ell}^{\ell} \sum_{t=\max(1, j+1)}^{\min(T, T+j)} \tilde{x}_{2it} \tilde{y}_{i, t-j} / (nT^2) \right].$$

The score bias correction is the same as the iterated correction because the first order conditions are linear in  $\theta$ .

The bias correction methods described above yield normal asymptotic distributions centered at the true parameter value for panels where  $n$  and  $T$  grow at the same rate with the sample size. This result is formally stated in Theorem 5, which establishes that all the methods are asymptotically equivalent, up to first order.

**Theorem 5** (Limit distribution of bias-corrected FE-GMM). *Assume that  $\sqrt{nT}(\hat{B}_s(\bar{\theta}) - B_s)/T \xrightarrow{p} 0$  and  $\sqrt{nT}(\hat{J}_s(\bar{\theta}) - J_s)/T \xrightarrow{p} 0$ , for some  $\bar{\theta} = \theta_0 + O_P((nT)^{-1/2})$ . Under Conditions 1, 2, 3, 4, 5 and 6, for  $C \in \{BC, SBC, IBC\}$*

$$(5.4) \quad \sqrt{nT}(\hat{\theta}^C - \theta_0) \xrightarrow{d} N(0, J_s^{-1}),$$

where  $\hat{\theta}^{BC}$ ,  $\hat{\theta}^{IBC}$  and  $\hat{\theta}^{SBC}$  are defined in (5.1), (5.2) and (5.3), and  $J_s = \bar{E}[G'_{\theta_i} P_{\alpha_i} G_{\theta_i}]$ .

The convergence condition for the estimators of  $B_s$  and  $J_s$  holds for sample analogs evaluated at the initial FE-GMM one-step or two-step estimators if the trimming sequence is chosen such that  $\ell \rightarrow \infty$  and  $\ell/T \rightarrow 0$  as  $T \rightarrow \infty$ . Theorem 5 also shows that all the bias-corrected estimators considered are first-order asymptotically efficient, since their variances achieve the semiparametric efficiency bound for the common parameters in this model, see Chamberlain (1992).

The following corollaries give bias corrected estimators for averages of the data and individual effects and for moments of the individual effects, together with the limit distributions of these estimators and consistent estimators of their asymptotic variances. To construct the corrections, we use bias corrected estimators of the common parameter. The corollaries then follow from Lemma 2 and Theorem 5 by the delta method. We use the same notation as in the estimation of the bias of the common parameters above to denote the estimators of the components of the bias and variance.

**Corollary 3** (Bias correction for fixed effects averages). *Let  $\zeta(z; \theta, \alpha_i)$  be a twice continuously differentiable function in its second and third argument, such that  $\inf_i \text{Var}[\zeta(z_{it})] > 0$ ,  $\bar{E}E[\zeta(z_{it})^2] < \infty$ ,  $\bar{E}E[\zeta_{\alpha}(z_{it})^2] < \infty$ , and  $\bar{E}E|\zeta_{\theta}(z_{it})|^2 < \infty$ . For  $C \in \{BC, SBC, IBC\}$ , let  $\hat{\zeta}^C = \hat{\zeta}(\hat{\theta}^C) - \hat{B}_{\zeta}(\hat{\theta}^C)/T$  where*

$$\hat{B}_{\zeta}(\theta) = \hat{E} \left[ \sum_{j=0}^{\ell} \frac{1}{T} \sum_{t=j+1}^T \hat{\zeta}_{\alpha_{it}}(\theta)' \hat{\psi}_{\alpha_{i,t-j}}(\theta) + \hat{\zeta}_{\alpha_i}(\theta)' \hat{B}_{\alpha_i}(\theta) + \sum_{j=1}^{d_{\alpha}} \hat{\zeta}_{\alpha\alpha_{i,j}}(\theta)' \hat{\Sigma}_{\alpha_i}(\theta)/2 \right],$$

where  $\ell$  is a positive bandwidth such that  $\ell \rightarrow \infty$  and  $\ell/T \rightarrow 0$  as  $T \rightarrow \infty$ . Then, under the conditions of Theorem 5

$$\sqrt{nT}(\hat{\zeta}^C - \zeta) \xrightarrow{d} N(0, V_{\zeta}),$$

where  $\zeta$  and  $V_{\zeta}$  are defined in Corollary 1. Also, for any  $\bar{\theta} = \theta_0 + O_P((nT)^{-1/2})$  and  $\bar{\zeta} = \zeta + O_P((nT)^{-1/2})$ ,

$$\hat{V}_{\zeta} = \hat{E}E[\hat{\zeta}_{\alpha_{it}}(\bar{\theta})' \hat{\Sigma}_{\alpha_i}(\bar{\theta}) \hat{\zeta}_{\alpha_{it}}(\bar{\theta}) + \hat{\zeta}_{\theta_{it}}(\bar{\theta})' \hat{J}_s(\bar{\theta})^{-1} \hat{\zeta}_{\theta_{it}}(\bar{\theta})] + \hat{E} \left[ \sum_{j=0}^{\ell} \frac{1}{T} \sum_{t=j+1}^T \{\hat{\zeta}_{it}(\bar{\theta}) - \bar{\zeta}\} \{\hat{\zeta}_{i,t-j}(\bar{\theta}) - \bar{\zeta}\} \right]$$

is a consistent estimator for  $V_{\zeta}$ .

**Corollary 4** (Bias correction for smooth functions of individual effects). *Let  $\mu(\alpha_i)$  be a twice differentiable function such that  $\bar{E}[\mu(\alpha_{i0})^2] < \infty$  and  $\bar{E}|\mu_{\alpha}(\alpha_{i0})|^2 < \infty$ . For  $C \in \{BC, SBC, IBC\}$ , let  $\hat{\mu}^C = \hat{E}[\hat{\mu}_i(\hat{\theta}^C)] - \hat{B}_{\mu}(\hat{\theta}^C)/T$ , where  $\hat{\mu}_i(\theta) = \mu(\hat{\alpha}_i(\theta))$ , and  $\hat{B}_{\mu}(\theta) = \hat{E}[\hat{\mu}_{\alpha_i}(\theta)' \hat{B}_{\alpha_i}(\theta) + \sum_{j=1}^{d_{\alpha}} \hat{\mu}_{\alpha\alpha_{i,j}}(\theta)' \hat{\Sigma}_{\alpha_i}(\theta)/2]$ . Then, under the conditions of Theorem 5*

$$\sqrt{n}(\hat{\mu}^C - \mu) \xrightarrow{d} N(0, V_{\mu}),$$

where  $\mu = \bar{E} [\mu(\alpha_{i0})]$  and  $V_\mu = \bar{E} [(\mu(\alpha_{i0}) - \mu)^2]$ . Also, for any  $\bar{\theta} = \theta_0 + O_P((nT)^{-1/2})$  and  $\bar{\mu} = \mu + O_P(n^{-1/2})$ ,

$$(5.5) \quad \hat{V}_\mu = \bar{E} \left[ \{\hat{\mu}_i(\bar{\theta}) - \bar{\mu}\}^2 + \hat{\mu}_{\alpha_i}(\bar{\theta})' \hat{\Sigma}_{\alpha_i}(\bar{\theta}) \hat{\mu}_{\alpha_i}(\bar{\theta}) / T \right],$$

is a consistent estimator for  $V_\mu$ . The second term in (5.5) is included to improve the finite sample properties of the estimator in short panels.

## 6. EMPIRICAL EXAMPLE

We illustrate the new estimators with an empirical example based on the classical cigarette demand study of Becker, Grossman and Murphy (1994) (BGM hereafter). Cigarettes are addictive goods. To account for this addictive nature, early cigarette demand studies included lagged consumption as explanatory variables (e.g., Baltagi and Levin, 1986). This approach, however, ignores that rational or forward-looking consumers take into account the effect of today's consumption decision on future consumption decisions. Becker and Murphy (1988) developed a model of rational addiction where expected changes in future prices affect the current consumption. BGM empirically tested this model using a linear structural demand function based on quadratic utility assumptions. The demand function includes both future and past consumptions as determinants of current demand, and the future price affects the current demand only through the future consumption. They found that the effect of future consumption on current consumption is significant, what they took as evidence in favor of the rational model.

Most of the empirical studies in this literature use yearly state-level panel data sets. They include fixed effects to control for additive heterogeneity at the state-level and use leads and lags of cigarette prices and taxes as instruments for leads and lags of consumption. These studies, however, do not consider possible non-additive heterogeneity in price elasticities or sensitivities across states. There are multiple reasons why there may be heterogeneity in the price effects across states correlated with the price level. First, the considerable differences in income, industrial, ethnic and religious composition at inter-state level can translate into different tastes and policies toward cigarettes. Second, from the perspective of the theoretical model developed by Becker and Murphy (1988), the price effect is a function of the marginal utility of wealth that varies across states and depends on cigarette prices. If the price effect is heterogenous and correlated with the price level, a fixed coefficient specification may produce substantial bias in estimating the average elasticity of cigarette consumption because the between variation of price is much larger than the within variation. Wangen (2004) gives additional theoretical reasons against a fixed coefficient specification for the demand function in this application.

We consider the following linear specification for the demand function

$$(6.1) \quad C_{it} = \alpha_{0i} + \alpha_{1i}P_{it} + \theta_1 C_{i,t-1} + \theta_2 C_{i,t+1} + X'_{it}\delta + \epsilon_{it},$$

where  $C_{it}$  is cigarette consumption in state  $i$  at time  $t$  measured by per capita sales in packs;  $\alpha_{0i}$  is an additive state effect;  $\alpha_{1i}$  is a state specific price coefficient;  $P_{it}$  is the price in 1982-1984 dollars; and  $X_{it}$  is a vector of covariates which includes income, various measures of incentive for smuggling across states, and year dummies. We estimate the model parameters using OLS and IV methods with both fixed coefficient for price and random coefficient for price. The data set, consisting of an unbalanced panel of 51 U.S. states over the years 1957 to 1994, is the same as in Fenn, Antonovitz and Schroeter (2001). The set of instruments for  $C_{i,t-1}$  and  $C_{i,t+1}$  in the IV estimators is the same as in specification 3 of BGM and includes  $X_{it}$ ,  $P_{it}$ ,  $P_{i,t-1}$ ,  $P_{i,t+1}$ ,  $Tax_{it}$ ,  $Tax_{i,t-1}$ , and  $Tax_{i,t+1}$ , where  $Tax_{it}$  is the state excise tax for cigarettes in 1982-1984 dollars.

Table 1 reports estimates of coefficients and demand elasticities. We focus on the coefficients of the key variables, namely  $P_{it}$ ,  $C_{i,t-1}$  and  $C_{i,t+1}$ . Throughout the table, FC refers to the fixed coefficient specification with  $\alpha_{1i} = \alpha_1$  and RC refers to the random coefficient specification in equation (6.1). BC and IBC refer to estimates after bias correction and iterated bias correction, respectively. Demand elasticities are calculated using the expressions in Appendix A of BGM. They are functions of  $C_{it}, P_{it}$ ,  $\alpha_{1i}$ ,  $\theta_1$  and  $\theta_2$ , linear in  $\alpha_{1i}$ . For random coefficient estimators, we report the mean of individual elasticities, i.e.

$$\hat{\zeta}_h = \frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T \zeta_h(z_{it}; \hat{\theta}, \hat{\alpha}_i),$$

where  $\zeta_h(z_{it}; \theta, \alpha_i) = \partial \log C_{it(h)} / \partial \log P_{it(h)}$  are price elasticities at different time horizons  $h$ . Standard errors for the elasticities are obtained by the delta method as described in Corollaries 3 and 4. For bias-corrected RC estimators the standard errors use bias-corrected estimates of  $\theta$  and  $\alpha_i$ .

As BGM, we find that OLS estimates substantially differ from their IV counterparts. IV-FC underestimates the elasticities relative to IV-RC. For example, the long-run elasticity estimate is  $-0.70$  with IV-FC, whereas it is  $-0.88$  with IV-RC. This difference is also pronounced for short-run elasticities, where the IV-RC estimates are more than 25 percent larger than the IV-FC estimates. We observe the same pattern throughout the table for every elasticity. The bias comes from both the estimation of the common parameter  $\theta_2$  and the mean of the individual specific parameter  $E[\alpha_{1i}]$ . The bias corrections increase the coefficient of future consumption  $C_{i,t+1}$  and reduce the absolute value of the mean of the price coefficient. Moreover, they have significant impact on the estimator of dispersion of the price coefficient. The uncorrected estimates of the standard deviation are more than



20% larger than the bias corrected counterparts. In the online appendix Fernández-Val and Lee (2012), we show through a Monte-Carlo experiment calibrated to this empirical example, that the bias is generally large for dispersion parameters and the bias corrections are effective in reducing this bias. As a consequence of shrinking the estimates of the dispersion of  $\alpha_{1i}$ , we obtain smaller standard errors for the estimates of  $E[\alpha_{1i}]$  throughout the table. In the Monte-Carlo experiment, we also find that this correction in the standard errors provides improved inference.

## 7. CONCLUSION

This paper introduces a new class of fixed effects GMM estimators for panel data models with unrestricted nonadditive heterogeneity and endogenous regressors. Bias correction methods are developed because these estimators suffer from the incidental parameters problem. Other estimators based on moment conditions, like the class of GEL estimators, can be analyzed using a similar methodology. An attractive alternative framework for estimation and inference in random coefficient models is a flexible Bayesian approach. It would be interesting to explore whether there are connections between moments of posterior distributions in the Bayesian approach and the fixed effects estimators considered in the paper. Another interesting extension would be to find bias reducing priors in the GMM framework similar to the ones characterized by Arellano and Bonhomme (2009) in the MLE framework. We leave these extensions to future research.

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**Table 1: Estimates of Rational Addiction Model for Cigarette Demand**

	OLS-FC	IV-FC	OLS-RC			IV-RC		
			NBC	BC	IBC	NBC	BC	IBC
Coefficients								
(Mean) $P_t$	-9.58 (1.86)	-34.10 (4.10)	-13.49 (3.55)	-13.58 (3.55)	-13.26 (3.55)	-36.39 (4.85)	-31.26 (4.62)	-31.26 (4.64)
(Std. Dev.) $P_t$			4.35 (0.98)	4.22 (1.02)	4.07 (1.03)	12.86 (2.35)	10.45 (2.13)	10.60 (2.15)
$C_{t-1}$	0.49 (0.01)	0.45 (0.06)	0.48 (0.04)	0.48 (0.04)	0.48 (0.04)	0.44 (0.04)	0.44 (0.04)	0.45 (0.04)
$C_{t+1}$	0.44 (0.01)	0.17 (0.07)	0.44 (0.04)	0.43 (0.04)	0.44 (0.04)	0.23 (0.05)	0.29 (0.05)	0.27 (0.05)
Price elasticities								
Long-run	-1.05 (0.24)	-0.70 (0.12)	-1.30 (0.28)	-1.31 (0.28)	-1.28 (0.28)	-0.88 (0.09)	-0.91 (0.10)	-0.90 (0.10)
Own Price (Anticipated)	-0.20 (0.04)	-0.32 (0.04)	-0.27 (0.06)	-0.27 (0.06)	-0.27 (0.06)	-0.38 (0.04)	-0.35 (0.04)	-0.35 (0.04)
Own Price (Unanticipated)	-0.11 (0.02)	-0.29 (0.03)	-0.15 (0.04)	-0.16 (0.04)	-0.15 (0.04)	-0.33 (0.04)	-0.29 (0.04)	-0.29 (0.04)
Future Price (Unanticipated)	-0.07 (0.01)	-0.05 (0.03)	-0.10 (0.02)	-0.10 (0.02)	-0.09 (0.02)	-0.09 (0.02)	-0.10 (0.02)	-0.09 (0.02)
Past Price (Unanticipated)	-0.08 (0.01)	-0.14 (0.02)	-0.11 (0.03)	-0.11 (0.02)	-0.10 (0.03)	-0.16 (0.02)	-0.15 (0.02)	-0.15 (0.02)
Short-Run	-0.30 (0.05)	-0.35 (0.06)	-0.41 (0.12)	-0.41 (0.12)	-0.40 (0.12)	-0.44 (0.06)	-0.44 (0.06)	-0.43 (0.06)

RC/FC refers to random/fixed coefficient model. NBC/BC/IBC refers to no bias-correction/bias correction/iterated bias correction estimates.

Note: *Standard errors are in parenthesis.*

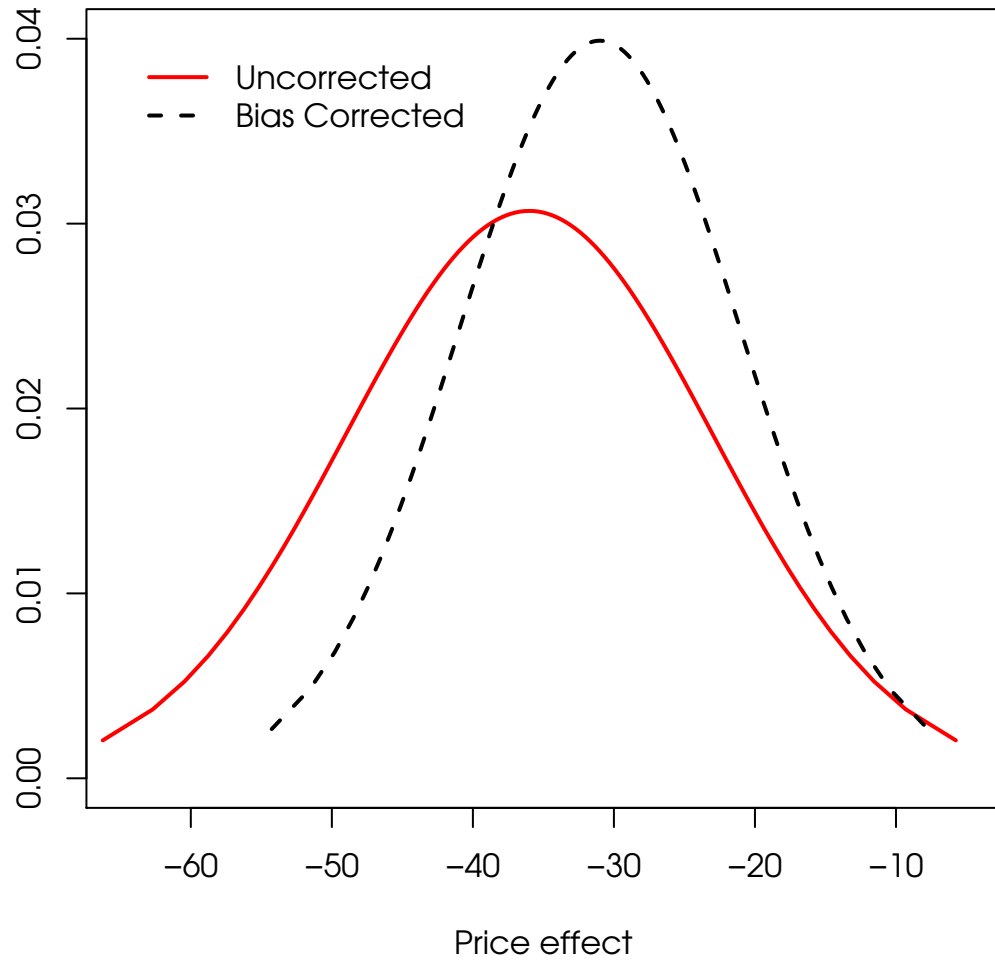


FIGURE 1. Normal approximation to the distribution of price effects using uncorrected (solid line) and bias corrected (dashed line) estimates of the mean and standard deviation of the distribution of price effects. Uncorrected estimates of the mean and standard deviation are -36 and 13, bias corrected estimates are -31 and 10.

# Supplementary Appendix to Panel Data Models with Nonadditive Unobserved Heterogeneity: Estimation and Inference

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This supplement to the paper “Panel Data Models with Nonadditive Unobserved Heterogeneity: Estimation and Inference” provides additional numerical examples and the proofs of the main results. The appendix is organized in seven sections. The first section contains a Monte Carlo simulation calibrated to the empirical example of the paper. The second section gives the proofs of the consistency of the one-step and two-step FE-GMM estimators. The third section includes the derivations of the asymptotic distribution of one-step and two-step FE-GMM estimators. The fourth section provides the derivations of the asymptotic distribution of bias corrected FE-GMM estimators. The fifth and sixth sections contain the characterization of the stochastic expansions for the estimators of the individual effects and the scores. The last section includes the expressions for the scores and their derivatives.

Throughout the appendices  $O_{uP}$  and  $o_{uP}$  will denote uniform orders in probability. For example, for a sequence of random variables  $\{\xi_i : 1 \leq i \leq n\}$ ,  $\xi_i = O_{uP}(1)$  means  $\sup_{1 \leq i \leq n} \xi_i = O_P(1)$ , and  $\xi_i = o_{uP}(1)$  means  $\sup_{1 \leq i \leq n} \xi_i = o_P(1)$ . It can be shown that the usual algebraic properties for  $O_P$  and  $o_P$  orders also apply to the uniform orders  $O_{uP}$  and  $o_{uP}$ . Let  $e_j$  denote a  $1 \times d_g$  unitary vector with a one in position  $j$ . For a matrix  $A$ ,  $|A|$  denotes Euclidean norm, that is  $|A|^2 = \text{trace}[AA']$ . HK refers to Hahn and Kuersteiner (2011).

## APPENDIX A. NUMERICAL EXAMPLE

We design a Monte Carlo experiment to closely match the cigarette demand empirical example in the paper. In particular, we consider the following linear model with common and individual specific parameters:

$$\begin{aligned} C_{it} &= \alpha_{0i} + \alpha_{1i}P_{it} + \theta_1 C_{i,t-1} + \theta_2 C_{i,t+1} + \psi \epsilon_{it}, \\ P_{it} &= \eta_{0i} + \eta_{1i}Tax_{it} + u_{it}, \quad (i = 1, 2, \dots, n, t = 1, 2, \dots, T); \end{aligned}$$

where  $\{(\alpha_{ji}, \eta_{ji}) : 1 \leq i \leq n\}$  is i.i.d. bivariate normal with mean  $(\mu_j, \mu_{\eta_j})$ , variances  $(\sigma_j^2, \sigma_{\eta_j}^2)$ , and correlation  $\rho_j$ , for  $j \in \{0, 1\}$ , independent across  $j$ ;  $\{u_{it} : 1 \leq t \leq T, 1 \leq i \leq n\}$  is i.i.d.  $N(0, \sigma_u^2)$ ; and  $\{\epsilon_{it} : 1 \leq t \leq T, 1 \leq i \leq n\}$  is i.i.d. standard normal. We fix the values of  $Tax_{it}$  to the values in the data set. All the parameters other than  $\rho_1$  and  $\psi$  are calibrated to the data set. Since the panel is balanced for only 1972 to 1994, we set  $T = 23$  and generate balanced panels for the simulations. Specifically, we consider

$$\begin{aligned} n = 51, T = 23; \mu_0 = 72.86, \mu_1 = -31.26, \mu_{\eta_0} = 0.81, \mu_{\eta_1} = 0.13, \sigma_0 = 18.54, \sigma_1 = 10.60, \sigma_{\eta_0} = 0.14, \\ \sigma_{\eta_1} = 2.05, \sigma_u = 0.15, \theta_1 = 0.45, \theta_2 = 0.27, \rho_0 = -0.17, \rho_1 \in \{0, 0.3, 0.6, 0.9\}, \psi \in \{2, 4, 6\}. \end{aligned}$$

In the empirical example, the estimated values of  $\rho_1$  and  $\psi$  are close to 0.3 and 5, respectively.

Since the model is dynamic with leads and lags of the dependent variable on the right hand side, we construct the series of  $C_{it}$  by solving the difference equation following BGM. The stationary part of the solution is

$$C_{it} = \frac{1}{\theta_1 \phi_1 (\phi_2 - \phi_1)} \sum_{s=1}^{\infty} \phi_1^s h_i(t+s) + \frac{1}{\theta_1 \phi_2 (\phi_2 - \phi_1)} \sum_{s=0}^{\infty} \phi_2^{-s} h_i(t-s)$$

where

$$h_i(t) = \alpha_{0i} + \alpha_{1i}P_{i,t-1} + \psi\epsilon_{i,t-1}, \quad \phi_1 = \frac{1 - (1 - 4\theta_1\theta_2)^{1/2}}{2\theta_1}, \quad \phi_2 = \frac{1 + (1 - 4\theta_1\theta_2)^{1/2}}{2\theta_1}.$$

In our specification, these values are  $\phi_1 = 0.31$  and  $\phi_2 = 1.91$ . The parameters that we vary across the experiments are  $\rho_1$  and  $\psi$ . The parameter  $\rho_1$  controls the degree of correlation between  $\alpha_{1i}$  and  $P_{it}$  and determines the bias caused by using fixed coefficient estimators. The parameter  $\psi$  controls the degree of endogeneity in  $C_{i,t-1}$  and  $C_{i,t+1}$ , which determines the bias of OLS and the incidental parameter bias of random coefficient IV estimators. Although  $\psi$  is not an ideal experimental parameter because it is the variance of the error, it is the only free parameter that affects the endogeneity of  $C_{i,t-1}$  and  $C_{i,t+1}$ . In this design we cannot fully remove the endogeneity of  $C_{i,t-1}$  and  $C_{i,t+1}$  because of the dynamics.

In each simulation, we estimate the parameters with standard fixed coefficient OLS and IV with additive individual effects (FC), and the FE-GMM OLS and IV estimators with the individual specific coefficients (RC). For IV, we use the same set of instruments as in the empirical example. We report results only for the common coefficient  $\theta_2$ , and the mean and standard deviation of the individual-specific coefficient  $\alpha_{1i}$ . Throughout the tables, *Bias* refers to the mean of the bias across simulations; *SD* refers to the standard deviation of the estimates; *SE/SD* denotes the ratio of the average standard error to the standard deviation; and *p; .05* is the rejection frequency of a two-sided test with nominal level of 0.05 that the parameter is equal to its true value. For bias-corrected RC estimators the standard errors are calculated using bias corrected estimates of the common parameter and individual effects.

Table A1 reports the results for the estimators of  $\theta_2$ . We find significant biases in all the OLS estimators and in the IV-FC estimators, relative to the standard deviations of these estimators. The bias of OLS depends only on  $\psi$ , whereas the bias of IV-RC depends only on  $\rho_1$ . When  $\rho_1 = 0$ , there is no correlation between  $\alpha_{1i}$  and  $P_{it}$ , and IV-FC estimates are consistent. As  $\rho_1$  increases the bias in IV-FC grows. IV-RC estimators have no bias in every configuration and their tests display much smaller size distortions than for the other estimators. The bias corrections preserve the bias and inference properties of the RC-IV estimator.

Table A2 reports similar results for the estimators of the mean of the individual specific coefficient  $\mu_1 = \bar{E}[\alpha_{1i}]$ . We find substantial biases for OLS and IV-FC estimators. RC-IV displays some bias, which is removed by the corrections in some configurations. The bias corrections provide significant improvements in the estimation of standard errors. IV-RC standard errors overestimate the dispersion by more than 15% when  $\psi$  is greater or equal than 4, whereas IV-BC or IV-IBC estimators have *SE/SD* ratios close to 1. As a result bias corrected estimators show smaller size distortions. This improvement comes from the bias correction in the estimates of the dispersion of  $\alpha_{1i}$  that we use to construct the standard errors. The bias of the estimator of the dispersion is generally large, and is effectively removed by the correction. We can see more evidence on this phenomenon in Table A3.

Table A3 shows the results for the estimators of the standard deviation of the individual specific coefficient  $\sigma_1 = \bar{E}[(\alpha_{1i} - \mu_1)^2]^{1/2}$ . As noted above, the bias corrections are relevant in this case. As  $\psi$  increases, the bias grows in orders of  $\psi^2$ . Most of bias is removed by the correction even when  $\psi$  is large. For example, when  $\psi = 6$ , the bias of IV-RC estimator is about 4 which is larger than two times its standard deviation. The correction reduces the bias to about 0.5, which is small relative to the standard deviation. Moreover, despite the overestimation in the standard errors, there are important size distortions for IV-RC estimators for tests on  $\sigma_1$  when  $\psi$  is large. The bias corrections bring the rejection frequencies close to their nominal levels.

Overall, the calibrated Monte-Carlo experiment confirms that the IV-RC estimator with bias correction provides improved estimation and inference for all the parameters of interest for the model considered in the empirical example.

## APPENDIX B. CONSISTENCY OF ONE-STEP AND TWO-STEP FE-GMM ESTIMATOR

**Lemma 3.** *Suppose that the Conditions 1 and 2 hold. Then, for every  $\eta > 0$*

$$\Pr \left\{ \sup_{1 \leq i \leq n} \sup_{(\theta, \alpha) \in \Upsilon} \left| \widehat{Q}_i^W(\theta, \alpha) - Q_i^W(\theta, \alpha) \right| \geq \eta \right\} = o(T^{-1}),$$

and

$$\sup_{\alpha} |Q_i^W(\theta, \alpha) - Q_i^W(\theta', \alpha)| \leq C \cdot E[M(z_{it})]^2 |\theta - \theta'|$$

for some constant  $C > 0$ .

*Proof.* First, note that

$$\begin{aligned} \left| \widehat{Q}_i^W(\theta, \alpha) - Q_i^W(\theta, \alpha) \right| &\leq \left| \widehat{g}_i(\theta, \alpha)' W_i^{-1} \widehat{g}_i(\theta, \alpha) - g_i(\theta, \alpha)' W_i^{-1} g_i(\theta, \alpha) \right| + \left| \widehat{g}_i(\theta, \alpha)' (\widehat{W}_i^{-1} - W_i^{-1}) \widehat{g}_i(\theta, \alpha) \right| \\ &\leq \left| [\widehat{g}_i(\theta, \alpha) - g_i(\theta, \alpha)]' W_i^{-1} [\widehat{g}_i(\theta, \alpha) - g_i(\theta, \alpha)] \right| + 2 \cdot \left| g_i(\theta, \alpha)' W_i^{-1} [\widehat{g}_i(\theta, \alpha) - g_i(\theta, \alpha)] \right| \\ &+ \left| [\widehat{g}_i(\theta, \alpha) - g_i(\theta, \alpha)]' (\widehat{W}_i^{-1} - W_i^{-1}) [\widehat{g}_i(\theta, \alpha) - g_i(\theta, \alpha)] \right| + 2 \left| [\widehat{g}_i(\theta, \alpha) - g_i(\theta, \alpha)]' (\widehat{W}_i^{-1} - W_i^{-1}) g_i(\theta, \alpha) \right| \\ &+ \left| g_i(\theta, \alpha)' (\widehat{W}_i^{-1} - W_i^{-1}) g_i(\theta, \alpha) \right| \leq d_g^2 \max_{1 \leq k \leq d_g} |\widehat{g}_{k,i}(\theta, \alpha) - g_{k,i}(\theta, \alpha)|^2 |W_i|^{-1} \\ &+ 2d_g^2 \sup_{1 \leq i \leq n} E[M(z_{it})] |W_i|^{-1} \max_{1 \leq k \leq d_g} |\widehat{g}_{k,i}(\theta, \alpha) - g_{k,i}(\theta, \alpha)| + o_P \left( \max_{1 \leq k \leq d_g} |\widehat{g}_{k,i}(\theta, \alpha) - g_{k,i}(\theta, \alpha)| \right), \end{aligned}$$

where we use that  $\sup_{1 \leq i \leq n} |\widehat{W}_i - W_i| = o_P(1)$ . Then, by Condition 2, we can apply Lemma 4 of HK to  $|\widehat{g}_{k,i}(\theta, \alpha) - g_{k,i}(\theta, \alpha)|$  to obtain the first part.

The second part follows from

$$\begin{aligned} |Q_i^W(\theta, \alpha) - Q_i^W(\theta', \alpha)| &\leq |g_i(\theta, \alpha)' W_i^{-1} [g_i(\theta, \alpha) - g_i(\theta', \alpha)]| + |[g_i(\theta, \alpha) - g_i(\theta', \alpha)]' W_i^{-1} g_i(\theta', \alpha)| \\ &\leq 2 \cdot d_g^2 E[M(z_{it})]^2 |W_i|^{-1} |\theta - \theta'|. \end{aligned}$$

□

### B.1. Proof of Theorem 1.

*Proof. Part I: Consistency of  $\tilde{\theta}$ .* For any  $\eta > 0$ , let  $\varepsilon := \inf_i [Q_i^W(\theta_0, \alpha_{i0}) - \sup_{\{(\theta, \alpha): |(\theta, \alpha) - (\theta_0, \alpha_{i0})| > \eta\}} Q_i^W(\theta, \alpha)] > 0$  as defined in Condition 2. Using the standard argument for consistency of extremum estimator, as in Newey and McFadden (1994), with probability  $1 - o(T^{-1})$

$$\max_{|\theta - \theta_0| > \eta, \alpha_1, \dots, \alpha_n} n^{-1} \sum_{i=1}^n \widehat{Q}_i^W(\theta, \alpha_i) < n^{-1} \sum_{i=1}^n \widehat{Q}_i^W(\theta_0, \alpha_{i0}) - \frac{1}{3} \varepsilon,$$

by definition of  $\varepsilon$  and Lemma 3. Thus, by continuity of  $\widehat{Q}_i^W$  and the definition of the lefthand side above, we conclude that  $\Pr \left[ \left| \tilde{\theta} - \theta_0 \right| \geq \eta \right] = o(T^{-1})$ .

**Part II: Consistency of  $\tilde{\alpha}_i$ .** By Part I and Lemma 3,

$$(B.1) \quad \Pr \left[ \sup_{1 \leq i \leq n} \sup_{\alpha} \left| \widehat{Q}_i^W(\tilde{\theta}, \alpha) - Q_i^W(\theta_0, \alpha) \right| \geq \eta \right] = o(T^{-1})$$



for any  $\eta > 0$ . Let

$$\varepsilon := \inf_i \left[ Q_i^W(\theta_0, \alpha_{i0}) - \sup_{\{\alpha_i: |\alpha_i - \alpha_{i0}| > \eta\}} Q_i^W(\theta_0, \alpha_i) \right] > 0.$$

Condition on the event

$$\left\{ \sup_{1 \leq i \leq n} \sup_{\alpha} \left| \widehat{Q}_i^W(\tilde{\theta}, \alpha) - Q_i^W(\theta_0, \alpha) \right| \leq \frac{1}{3} \varepsilon \right\},$$

which has a probability equal to  $1 - o(T^{-1})$  by (B.1). Then

$$\max_{|\alpha_i - \alpha_{i0}| > \eta} \widehat{Q}_i^W(\tilde{\theta}, \alpha_i) < \max_{|\alpha_i - \alpha_{i0}| > \eta} Q_i^W(\theta_0, \alpha_i) + \frac{1}{3} \varepsilon < Q_i^W(\theta_0, \alpha_{i0}) - \frac{2}{3} \varepsilon < \widehat{Q}_i^W(\tilde{\theta}, \alpha_{i0}) - \frac{1}{3} \varepsilon.$$

This is inconsistent with  $\widehat{Q}_i^W(\tilde{\theta}, \tilde{\alpha}_i) \geq \widehat{Q}_i^W(\tilde{\theta}, \alpha_{i0})$ , and therefore,  $|\tilde{\alpha}_i - \alpha_{i0}| \leq \eta$  with probability  $1 - o(T^{-1})$  for every  $i$ .

**Part III: Consistency of  $\tilde{\lambda}_i$ .** First, note that

$$\begin{aligned} |\tilde{\lambda}_i| &= \left| \widehat{W}_i^{-1} \widehat{g}_i(\tilde{\theta}, \tilde{\alpha}_i) \right| \leq d_g \left| \widehat{W}_i \right|^{-1} \max_{1 \leq k \leq d_g} \left( \left| \widehat{g}_{k,i}(\tilde{\theta}, \tilde{\alpha}_i) - g_{k,i}(\tilde{\theta}, \tilde{\alpha}_i) \right| + \left| g_{k,i}(\tilde{\theta}, \tilde{\alpha}_i) \right| \right) \\ &\leq d_g \left| \widehat{W}_i \right|^{-1} \max_{1 \leq k \leq d_g} \sup_{(\theta, \alpha_i) \in \Upsilon} \left| \widehat{g}_{k,i}(\theta, \alpha_i) - g_{k,i}(\theta, \alpha_i) \right| \\ &\quad + d_g \left| \widehat{W}_i \right|^{-1} M(z_{it}) \left| \tilde{\theta} - \theta_0 \right| + d_g \left| \widehat{W}_i \right|^{-1} M(z_{it}) |\tilde{\alpha}_i - \alpha_{i0}|. \end{aligned}$$

Then, the result follows because  $\sup_{1 \leq i \leq n} |\widehat{W}_i - W_i| = o_P(1)$  and  $\{W_i : 1 \leq i \leq n\}$  are positive definite by Condition 2,  $\max_{1 \leq k \leq d_g} \sup_{(\theta, \alpha_i) \in \Upsilon} |\widehat{g}_{k,i}(\theta, \alpha_i) - g_{k,i}(\theta, \alpha_i)| = o_P(1)$  by Lemma 4 in HK, and  $|\tilde{\theta} - \theta_0| = o_P(1)$  and  $\sup_{1 \leq i \leq n} |\tilde{\alpha}_i - \alpha_{i0}| = o_P(1)$  by Parts I and II.  $\square$

## B.2. Proof of Theorem 3.

*Proof.* First, assume that Conditions 1, 2, 3 and 5 hold. The proofs are exactly the same as that of Theorem 1 using the uniform convergence of the criterion function.

To establish the uniform convergence of the criterion function as in Lemma 3, we need

$$\sup_{1 \leq i \leq n} \left| \widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) - \Omega_i(\theta_0, \alpha_{i0}) \right| = o_P(1),$$

along with an extended version of the continuous mapping theorem for  $o_{uP}$ . This can be shown by noting that

$$\begin{aligned} \left| \widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) - \Omega_i(\theta_0, \alpha_{i0}) \right| &\leq \left| \widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) - \Omega_i(\tilde{\theta}, \tilde{\alpha}_i) \right| + \left| \Omega_i(\tilde{\theta}, \tilde{\alpha}_i) - \Omega_i(\theta_0, \alpha_{i0}) \right| \\ &\leq \left| \widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) - \Omega_i(\tilde{\theta}, \tilde{\alpha}_i) \right| + d_g^2 E \left[ M(z_{it})^2 \right] \left| (\tilde{\theta}, \tilde{\alpha}_i) - (\theta_0, \alpha_{i0}) \right|. \end{aligned}$$

The convergence follows by the consistency of  $\tilde{\theta}$  and  $\tilde{\alpha}_i$ 's, and the application of Lemma 2 of HK to  $g_k(z_{it}; \theta, \alpha_i) g_l(z_{it}; \theta, \alpha_i)$  using that  $|g_k(z_{it}; \theta, \alpha_i) g_l(z_{it}; \theta, \alpha_i)| \leq M(z_{it})^2$ .  $\square$

## APPENDIX C. ASYMPTOTIC DISTRIBUTION OF ONE-STEP AND TWO-STEP FE-GMM ESTIMATOR

### C.1. Some Lemmas.

**Lemma 4.** Assume that Condition 1 holds. Let  $h(z_{it}; \theta, \alpha_i)$  be a function such that (i)  $h(z_{it}; \theta, \alpha_i)$  is continuously differentiable in  $(\theta, \alpha_i) \in \Upsilon \subset \mathbb{R}^{d_\theta + d_\alpha}$ ; (ii)  $\Upsilon$  is convex; (iii) there exists a function  $M(z_{it})$  such that  $|h(z_{it}; \theta, \alpha_i)| \leq M(z_{it})$  and  $|\partial h(z_{it}; \theta, \alpha_i) / \partial(\theta, \alpha_i)| \leq M(z_{it})$  with  $E \left[ M(z_{it})^{5(d_\theta + d_\alpha + 6)/(1-10v) + \delta} \right] < \infty$

for some  $\delta > 0$  and  $0 < v < 1/10$ . Define  $\hat{H}_i(\theta, \alpha_i) := T^{-1} \sum_{t=1}^T h(z_{it}; \theta, \alpha_i)$ , and  $H_i(\theta, \alpha_i) := E[\hat{H}_i(\theta, \alpha_i)]$ . Let

$$\alpha_i^* = \arg \max_{\alpha_i} \hat{Q}_i^W(\theta^*, \alpha_i),$$

such that  $\alpha_i^* - \alpha_{i0} = o_{uP}(T^{a_\alpha})$  and  $\theta^* - \theta_0 = o_P(T^{a_\theta})$ , with  $-2/5 \leq a \leq 0$ , for  $a = \max(a_\alpha, a_\theta)$ . Then, for any  $\bar{\theta}$  between  $\theta^*$  and  $\theta_0$ , and  $\bar{\alpha}_i$  between  $\alpha_i^*$  and  $\alpha_{i0}$ ,

$$\sqrt{T}[\hat{H}_i(\bar{\theta}, \bar{\alpha}_i) - H_i(\bar{\theta}, \bar{\alpha}_i)] = o_{uP}(T^{1/10}), \quad \hat{H}_i(\bar{\theta}, \bar{\alpha}_i) - H_i(\theta_0, \alpha_{i0}) = o_{uP}(T^a).$$

*Proof.* The first statement follows from Lemma 2 in HK. The second statement follows by the first statement and the conditions of the Lemma by a mean value expansion since

$$\begin{aligned} \left| \hat{H}_i(\bar{\theta}, \bar{\alpha}_i) - H_i(\theta_0, \alpha_{i0}) \right| &\leq \underbrace{\left| \bar{\theta} - \theta_0 \right|}_{=o_{uP}(T^a)} \underbrace{\left| \frac{1}{T} \sum_{t=1}^T M(z_{it}) \right|}_{=O_{uP}(1)} + \underbrace{\left| \bar{\alpha}_i - \alpha_{i0} \right|}_{=o_{uP}(T^a)} \underbrace{\left| \frac{1}{T} \sum_{t=1}^T M(z_{it}) \right|}_{=O_{uP}(1)} \\ &\quad + \underbrace{\left| \hat{H}_i(\theta_0, \alpha_{i0}) - H_i(\theta_0, \alpha_{i0}) \right|}_{=o_{uP}(T^{-2/5})} = o_{uP}(T^a). \end{aligned}$$

□

**Lemma 5.** Assume that Conditions 1, 2, 3 and 4 hold. Let  $\hat{t}_i^W(\theta, \gamma_i)$  denote the first stage GMM score of the fixed effects, that is

$$\hat{t}_i^W(\theta, \gamma_i) = - \begin{pmatrix} \hat{G}_{\alpha_i}(\theta, \alpha_i)' \lambda_i \\ \hat{g}_i(\theta, \alpha_i) + \hat{W}_i \lambda_i \end{pmatrix},$$

where  $\gamma_i = (\alpha_i', \lambda_i')'$ ,  $\hat{s}_i^W(\theta, \gamma_i)$  denote the one-step GMM score for the common parameter, that is

$$\hat{s}_i^W(\theta, \gamma_i) = -\hat{G}_{\theta i}(\theta, \alpha_i)' \lambda_i,$$

and  $\tilde{\gamma}_i(\theta)$  be such that  $\hat{t}_i^W(\theta, \tilde{\gamma}_i(\theta)) = 0$ .

Let  $\hat{T}_{i,j}^W(\theta, \gamma_i)$  denote  $\partial \hat{t}_i^W(\theta, \gamma_i) / \partial \gamma_i' \partial \gamma_{i,j}$  and  $\hat{M}_{i,j}^W(\theta, \gamma_i)$  denote  $\partial \hat{s}_i^W(\theta, \gamma_i) / \partial \gamma_i' \partial \gamma_{i,j}$ , for some  $0 \leq j \leq d_g + d_\alpha$ , where  $\gamma_{i,j}$  is the  $j$ th element of  $\gamma_i$  and  $j = 0$  denotes no second derivative. Let  $\hat{N}_i^W(\theta, \gamma_i)$  denote  $\partial \hat{t}_i^W(\theta, \gamma_i) / \partial \theta'$  and  $\hat{S}_i^W(\theta, \gamma_i)$  denote  $\partial \hat{s}_i^W(\theta, \gamma_i) / \partial \theta'$ . Let  $(\tilde{\theta}, \tilde{\gamma}_1, \dots, \tilde{\gamma}_n)$  be the one-step GMM estimator. Then, for any  $\bar{\theta}$  between  $\tilde{\theta}$  and  $\theta_0$ , and  $\bar{\gamma}_i$  between  $\tilde{\gamma}_i$  and  $\gamma_{i0}$ ,

$$\hat{T}_{i,j}^W(\bar{\theta}, \bar{\gamma}_i) - T_{i,j}^W = o_{uP}(1), \quad \hat{M}_{i,j}^W(\bar{\theta}, \bar{\gamma}_i) - M_{i,j}^W = o_{uP}(1), \quad \hat{N}_i^W(\bar{\theta}, \bar{\gamma}_i) - N_i^W = o_{uP}(1), \quad \hat{S}_i^W(\bar{\theta}, \bar{\gamma}_i) - S_i^W = o_{uP}(1).$$

Also, for any  $\bar{\gamma}_{i0}$  between  $\gamma_{i0}$  and  $\tilde{\gamma}_{i0} = \tilde{\gamma}_i(\theta_0)$ ,

$$\begin{aligned} \sqrt{T} \hat{t}_i^W(\theta_0, \bar{\gamma}_{i0}) &= o_{uP}(T^{1/10}), \quad \sqrt{T} (\hat{T}_{i,j}^W(\theta_0, \bar{\gamma}_{i0}) - T_{i,j}^W) = o_{uP}(T^{1/10}), \\ \sqrt{T} (\hat{M}_{i,j}^W(\theta_0, \bar{\gamma}_{i0}) - M_{i,j}^W) &= o_{uP}(T^{1/10}), \end{aligned}$$

*Proof.* The first set of results follows by inspection of the scores and their derivatives (the expressions are given in Appendix G), uniform consistency of  $\tilde{\gamma}_i$  by Theorem 1 and application of the first part of Lemma 4 to  $\theta^* = \tilde{\theta}$  and  $\alpha_i^* = \tilde{\alpha}_i$  with  $a = 0$ .

The following steps are used to prove the second set of result. By Lemma 4,

$$\sqrt{T} \hat{t}_i^W = o_{uP}(T^{1/10}), \quad \hat{T}_i^W(\theta_0, \bar{\gamma}_{i0}) - T_i^W = o_{uP}(1)$$

where  $\bar{\gamma}_{i0}$  is between  $\tilde{\gamma}_{i0}$  and  $\gamma_{i0}$ . Then, a mean value expansion of the FOC of  $\tilde{\gamma}_{i0}$ ,  $\hat{t}_i^W(\theta_0, \tilde{\gamma}_{i0}) = 0$ , around  $\tilde{\gamma}_{i0} = \gamma_{i0}$  gives

$$\begin{aligned} \sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}) &= -\underbrace{(T_i^W)^{-1}}_{=O_u(1)} \underbrace{\sqrt{T}\hat{t}_i^W}_{=o_{uP}(T^{1/10})} - \underbrace{(T_i^W)^{-1}}_{=O_u(1)} \underbrace{(\hat{T}_i^W(\theta_0, \bar{\gamma}_{i0}) - T_i^W)}_{=o_{uP}(1)} \sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}) \\ &= o_{uP}(T^{1/10}) + o_{uP}\left(\sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0})\right), \end{aligned}$$

by Condition 3 and the previous result. Therefore,

$$(1 + o_{uP}(1)) \sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}) = o_{uP}(T^{1/10}) \Rightarrow \sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}) = o_{uP}(T^{1/10}).$$

Given this uniform rate for  $\tilde{\gamma}_{i0}$ , the desired result can be obtained by applying the second part of Lemma 4 to  $\theta^* = \theta_0$  and  $\alpha_i^* = \tilde{\alpha}_{i0}$  with  $a = -2/5$ .  $\square$

## C.2. Proof of Theorem 2.

*Proof.* By a mean value expansion of the FOC for  $\tilde{\theta}$  around  $\tilde{\theta} = \theta_0$ ,

$$0 = \hat{s}^W(\tilde{\theta}) = \hat{s}^W(\theta_0) + \frac{d\hat{s}^W(\bar{\theta})}{d\theta'}(\tilde{\theta} - \theta_0),$$

where  $\bar{\theta}$  lies between  $\tilde{\theta}$  and  $\theta_0$ .

**Part I:** Asymptotic limit of  $d\hat{s}^W(\bar{\theta})/d\theta'$ . Note that

$$\begin{aligned} \frac{d\hat{s}^W(\bar{\theta})}{d\theta'} &= \frac{1}{n} \sum_{i=1}^n \frac{d\hat{s}_i^W(\bar{\theta}, \tilde{\gamma}_i(\bar{\theta}))}{d\theta'}, \\ \frac{d\hat{s}_i^W(\bar{\theta}, \tilde{\gamma}_i(\bar{\theta}))}{d\theta'} &= \frac{\partial \hat{s}_i^W(\bar{\theta}, \tilde{\gamma}_i(\bar{\theta}))}{\partial \theta'} + \frac{\partial \hat{s}_i^W(\bar{\theta}, \tilde{\gamma}_i(\bar{\theta}))}{\partial \gamma'_i} \frac{\partial \tilde{\gamma}_i(\bar{\theta})}{\theta'}. \end{aligned} \quad (\text{C.1})$$

By Lemma 5,

$$\frac{\partial \hat{s}_i^W(\bar{\theta}, \tilde{\gamma}_i(\bar{\theta}))}{\partial \theta'} = S_i^W + o_{uP}(1), \quad \frac{\partial \hat{s}_i^W(\bar{\theta}, \tilde{\gamma}_i(\bar{\theta}))}{\partial \gamma'_i} = M_i^W + o_{uP}(1).$$

Then, differentiation of the FOC for  $\tilde{\gamma}_i(\bar{\theta})$ ,  $\hat{t}_i^W(\bar{\theta}, \tilde{\gamma}_i(\bar{\theta})) = 0$ , with respect to  $\theta$  and  $\tilde{\gamma}_i$  gives

$$\hat{T}_i^W(\bar{\theta}, \tilde{\gamma}_i(\bar{\theta})) \frac{\partial \tilde{\gamma}_i(\bar{\theta})}{\partial \theta'} + \hat{N}_i^W(\bar{\theta}, \tilde{\gamma}_i(\bar{\theta})) = 0,$$

By repeated application of Lemma 5 and Condition 3,

$$\frac{\partial \tilde{\gamma}_i(\bar{\theta})}{\partial \theta'} = -(T_i^W)^{-1} N_i^W + o_{uP}(1).$$

Finally, replacing the expressions for the components in (C.1) and using the formulae for the derivatives, which are provided in the Appendix G,

$$\frac{d\hat{s}^W(\bar{\theta})}{d\theta'} = \frac{1}{n} \sum_{i=1}^n G'_{\theta_i} P_{\alpha_i}^W G_{\theta_i} + o_P(1) = J_s^W + o_P(1), \quad J_s^W = \bar{E}[G'_{\theta_i} P_{\alpha_i}^W G_{\theta_i}]. \quad (\text{C.2})$$

**Part II:** Asymptotic Expansion for  $\tilde{\theta} - \theta_0$ . By (C.2) and Lemma 22, which states the stochastic expansion of  $\sqrt{nT}\hat{s}^W(\theta_0)$ ,

$$0 = \underbrace{\sqrt{nT}\hat{s}^W(\theta_0)}_{O_P(1)} + \underbrace{\frac{d\hat{s}^W(\bar{\theta})}{d\theta'}}_{O_P(1)} \sqrt{nT}(\tilde{\theta} - \theta_0).$$

Therefore,  $\sqrt{nT}(\tilde{\theta} - \theta_0) = O_P(1)$ , and by part I, Lemma 22 and Condition 3,

$$\sqrt{nT}(\tilde{\theta} - \theta_0) \xrightarrow{d} -(J_s^W)^{-1} N(\kappa B_s^W, V_s^W).$$

□

### C.3. Proof of Theorem 4.

*Proof.* Applying Lemma 4 with a minor modification, along with Condition 4, we can prove an exact counterpart to Lemma 5 for the two-step GMM score for the fixed effects

$$\hat{t}_i(\theta, \gamma_i) = \hat{t}_i^\Omega(\theta, \gamma_i) + \hat{t}_i^R(\theta, \gamma_i),$$

where the expressions of  $\hat{t}_i^\Omega$  and  $\hat{t}_i^R$  are given in the Appendix G, and for the two-step score of the common parameter

$$\hat{s}_i(\theta, \hat{\gamma}_i(\theta)) = -\hat{G}_{\theta i}(\theta, \hat{\alpha}_i(\theta))' \hat{\lambda}_i(\theta),$$

The only difference arises due to the term  $\hat{t}_i^R(\theta, \gamma_i)$ , which involves  $\hat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) - \Omega_i$ . Lemma 8 shows that  $\sqrt{T}(\hat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) - \Omega_i) = o_{uP}(T^{1/10})$ , so that a result similar to Lemma 5 holds for the two-step scores.

Thus, we can make the same argument as in the proof of Theorem 2 using the stochastic expansion of  $\sqrt{nT}\hat{s}(\theta_0)$  given in Lemma 23. □

## APPENDIX D. ASYMPTOTIC DISTRIBUTION OF BIAS-CORRECTED TWO-STEP GMM ESTIMATOR

### D.1. Some Lemmas.

**Lemma 6.** Assume that Conditions 1, 2, 3, 4 and 5 hold. Let  $\hat{t}_i(\theta, \gamma_i)$  denote the two-step GMM score for the fixed effects,  $\hat{s}_i(\theta, \gamma_i)$  denote the two-step GMM score for the common parameter, and  $\hat{\gamma}_i(\theta)$  be such that  $\hat{t}_i(\theta, \hat{\gamma}_i(\theta)) = 0$ . Let  $\hat{T}_{i,j}(\theta, \gamma_i)$  denote  $\partial \hat{t}_i(\theta, \gamma_i) / \partial \gamma_i' \partial \gamma_{i,j}$ , for some  $0 \leq j \leq d_g + d_\alpha$ , where  $\gamma_{i,j}$  is the  $j$ th component of  $\gamma_i$  and  $j = 0$  denotes no second derivative. Let  $\hat{N}_i(\theta, \gamma_i)$  denote  $\partial \hat{t}_i(\theta, \gamma_i) / \partial \theta'$ . Let  $\hat{M}_{i,j}(\theta, \gamma_i)$  denote  $\partial \hat{s}_i(\theta, \gamma_i) / \partial \gamma_i' \partial \gamma_{i,j}$ , for some  $0 \leq j \leq d_g + d_\alpha$ . Let  $\hat{S}_i(\theta, \gamma_i)$  denote  $\partial \hat{s}_i(\theta, \gamma_i) / \partial \theta'$ . Let  $(\hat{\theta}, \{\hat{\gamma}_i\}_{i=1}^n)$  be the two-step GMM estimators.

Then, for any  $\bar{\theta}$  between  $\hat{\theta}$  and  $\theta_0$ , and  $\bar{\gamma}_i$  between  $\hat{\gamma}_i$  and  $\gamma_{i0}$ ,

$$\begin{aligned} \sqrt{T}(\hat{T}_{i,d}(\bar{\theta}, \bar{\gamma}_i) - T_{i,d}) &= o_{uP}(T^{1/10}), \quad \sqrt{T}(\hat{M}_{i,j}(\bar{\theta}, \bar{\gamma}_i) - M_{i,j}) = o_{uP}(T^{1/10}), \\ \sqrt{T}(\hat{N}_i(\bar{\theta}, \bar{\gamma}_i) - N_i) &= o_{uP}(T^{1/10}), \quad \sqrt{T}(\hat{S}_i(\bar{\theta}, \bar{\gamma}_i) - S_i) = o_{uP}(T^{1/10}). \end{aligned}$$

*Proof.* Let  $\hat{\gamma}_i = \hat{\gamma}_i(\hat{\theta})$  and  $\hat{\gamma}_{i0} = \hat{\gamma}_i(\theta_0)$ . First, note that

$$\sqrt{T}(\hat{\gamma}_i - \hat{\gamma}_{i0}) = \frac{\partial \hat{\gamma}_i(\bar{\theta})}{\partial \theta'} \sqrt{T}(\hat{\theta} - \theta_0) = \underbrace{-(T_i^\Omega)^{-1} N_i}_{=O_u(1)} \underbrace{\sqrt{T}(\hat{\theta} - \theta_0)}_{=O_P(n^{-1/2})} + o_{uP}(\sqrt{T}(\hat{\theta} - \theta_0)) = O_{uP}(n^{-1/2}).$$

where the second equality follows from the proof of Theorem 2 and 4. Thus, by the same argument used in the proof of Lemma 5,

$$\sqrt{T}(\hat{\gamma}_i - \gamma_{i0}) = \sqrt{T}(\hat{\gamma}_i - \hat{\gamma}_{i0}) + \sqrt{T}(\hat{\gamma}_{i0} - \gamma_{i0}) = o_{uP}(T^{1/10}).$$

Given this result and inspection of the scores and their derivatives (see the Appendix G), the proof is similar to the proof of the second part of Lemma 5. □

**Lemma 7.** Assume that Condition 1 holds. Let  $h_j(z_{it}; \theta, \alpha_i)$ ,  $j = 1, 2$  be two functions such that (i)  $h_j(z_{it}; \theta, \alpha_i)$  is continuously differentiable in  $(\theta, \alpha_i) \in \Upsilon \subset \mathbb{R}^{d_\theta + d_\alpha}$ ; (ii)  $\Upsilon$  is convex; (iii) there exists a function  $M(z_{it})$  such that  $|h_j(z_{it}; \theta, \alpha_i)| \leq M(z_{it})$  and  $|\partial h_j(z_{it}; \theta, \alpha_i) / \partial(\theta, \alpha_i)| \leq M(z_{it})$  with  $E[M(z_{it})^{10(d_\theta + d_\alpha + 6)/(1-10v) + \delta}] < \infty$  for some  $\delta > 0$  and  $0 < v < 1/10$ . Define  $\hat{F}_i(\theta, \alpha_i) := T^{-1} \sum_{t=1}^T h_1(z_{it}; \theta, \alpha_i) h_2(z_{it}; \theta, \alpha_i)$ , and  $F_i(\theta, \alpha_i) := E[\hat{F}_i(\theta, \alpha_i)]$ . Let

$$\alpha_i^* = \arg \sup_{\alpha} \hat{Q}_i^W(\theta^*, \alpha),$$

such that  $\alpha_i^* - \alpha_{i0} = o_{uP}(T^{a_\alpha})$  and  $\theta^* - \theta_0 = o_P(T^{a_\theta})$ , with  $-2/5 \leq a \leq 0$ , for  $a = \max(a_\alpha, a_\theta)$ . Then, for any  $\bar{\theta}$  between  $\theta^*$  and  $\theta_0$ , and  $\bar{\alpha}_i$  between  $\alpha_i^*$  and  $\alpha_{i0}$ ,

$$\hat{F}_i(\bar{\theta}, \bar{\alpha}_i) - F_i(\theta_0, \alpha_{i0}) = o_{uP}(T^a), \quad \sqrt{T}[\hat{F}_i(\bar{\theta}, \bar{\alpha}_i) - F_i(\bar{\theta}, \bar{\alpha}_i)] = o_{uP}(T^{1/10}).$$

*Proof.* Same as for Lemma 4, replacing  $H_i$  by  $F_i$ , and  $M(z_{it})$  by  $M(z_{it})^2$ . □

**Lemma 8.** Assume that Conditions 1, 2, 3, 4, 5, and 6 hold. Let  $\hat{\Omega}_i(\bar{\theta}, \bar{\alpha}_i) = T^{-1} \sum_{t=1}^T g(z_{it}; \bar{\theta}, \bar{\alpha}_i) g(z_{it}; \bar{\theta}, \bar{\alpha}_i)'$  be an estimator of the covariance function  $\Omega_i = E[g(z_{it}) g(z_{it})']$ , where  $\bar{\theta} = \theta_0 + o_P(T^{-2/5})$  and  $\bar{\alpha}_i = \alpha_{i0} + o_{uP}(T^{-2/5})$ . Let  $\hat{\Omega}_{\alpha^{d_1} \theta^{d_2}}(\bar{\theta}, \bar{\alpha}_i) = \partial^{d_1+d_2} \hat{\Omega}_i(\bar{\theta}, \bar{\alpha}_i) / \partial^{d_1} \alpha_i \partial^{d_2} \theta$ , for  $0 \leq d_1 + d_2 \leq 2$ . Then,

$$\sqrt{T} \left( \hat{\Omega}_{\alpha^{d_1} \theta^{d_2}}(\bar{\theta}, \bar{\alpha}_i) - \Omega_{\alpha^{d_1} \theta^{d_2}} \right) = o_{uP}(T^{1/10}).$$

*Proof.* Note that

$$\begin{aligned} & |g(z_{it}; \bar{\theta}, \bar{\alpha}_i) g(z_{it}; \bar{\theta}, \bar{\alpha}_i)' - E[g(z_{it}; \bar{\theta}, \bar{\alpha}_i) g(z_{it}; \bar{\theta}, \bar{\alpha}_i)']| \\ & \leq d_g^2 \max_{1 \leq k \leq l \leq d_g} |g_k(z_{it}; \bar{\theta}, \bar{\alpha}_i) g_l(z_{it}; \bar{\theta}, \bar{\alpha}_i)' - E[g_k(z_{it}; \bar{\theta}, \bar{\alpha}_i) g_l(z_{it}; \bar{\theta}, \bar{\alpha}_i)']|. \end{aligned}$$

Then we can apply Lemma 7 to  $h_1 = g_k$  and  $h_2 = g_l$  with  $a = -2/5$ . A similar argument applies to the derivatives, since they are sums of products of elements that satisfy the assumption of Lemma 7. □

**Lemma 9.** Assume that Conditions 1, 2, 3, 4, 5, and 6 hold, and  $\ell \rightarrow \infty$  such that  $\ell/T \rightarrow 0$  as  $T \rightarrow \infty$ . For any  $\bar{\theta}$  such that between  $\hat{\theta}$  and  $\theta_0$ , let  $\hat{\Sigma}_{\alpha_i}(\bar{\theta}) = [\hat{G}_{\alpha_i}(\bar{\theta})' \hat{\Omega}_i^{-1} \hat{G}_{\alpha_i}(\bar{\theta})]^{-1}$ ,  $\hat{H}_{\alpha_i}(\bar{\theta}) = \hat{\Sigma}_{\alpha_i}(\bar{\theta}) \hat{G}_{\alpha_i}(\bar{\theta})' \hat{\Omega}_i^{-1}$ ,  $\hat{P}_{\alpha_i}(\bar{\theta}) = \hat{\Omega}_i^{-1} - \hat{\Omega}_i^{-1} \hat{G}_{\alpha_i}(\bar{\theta}) \hat{H}_{\alpha_i}(\bar{\theta})$ ,  $\hat{\Sigma}_{\alpha_i}^W(\bar{\theta}) = [\hat{G}_{\alpha_i}(\bar{\theta})' W_i^{-1} \hat{G}_{\alpha_i}(\bar{\theta})]^{-1}$ ,  $\hat{H}_{\alpha_i}^W(\bar{\theta}) = \hat{\Sigma}_{\alpha_i}^W(\bar{\theta}) \hat{G}_{\alpha_i}(\bar{\theta})' W_i^{-1}$ ,  $\hat{J}_{si}(\bar{\theta}) = \hat{G}_{\theta_i}(\bar{\theta})' \hat{P}_{\alpha_i}(\bar{\theta}) \hat{G}_{\theta_i}(\bar{\theta})$ ,  $\hat{B}_{si}^C(\bar{\theta}) = T^{-1} \sum_{j=0}^{\ell} \sum_{t=j+1}^T \hat{G}_{\theta_{it}}(\bar{\theta})' \hat{P}_{\alpha_i}(\bar{\theta}) \hat{g}_{i,t-j}(\bar{\theta})$ , and  $\hat{B}_{si}^B(\bar{\theta}) = -\hat{G}_{\theta_i}(\bar{\theta})' [\hat{B}_{\lambda_i}^I(\bar{\theta}) + \hat{B}_{\lambda_i}^G(\bar{\theta}) + \hat{B}_{\lambda_i}^\Omega(\bar{\theta}) + \hat{B}_{\lambda_i}^W(\bar{\theta})]$ , where

$$\begin{aligned} \hat{B}_{\lambda_i}^I(\theta) &= -\hat{P}_{\alpha_i}(\theta) \sum_{j=1}^{d_\alpha} \hat{G}_{\alpha \alpha_{i,j}}(\theta) \hat{\Sigma}_{\alpha_i}(\theta) / 2 + \hat{P}_{\alpha_i}(\theta) \sum_{j=0}^{\ell} T^{-1} \sum_{t=j+1}^T \hat{G}_{\alpha_{it}}(\theta) \hat{H}_{\alpha_i}(\theta) \hat{g}_{i,t-j}(\theta), \\ \hat{B}_{\lambda_i}^G(\theta) &= \hat{H}_{\alpha_i}(\theta)' \sum_{j=0}^{\infty} T^{-1} \sum_{t=j+1}^T \hat{G}_{\alpha_{it}}(\theta)' \hat{P}_{\alpha_i}(\theta) \hat{g}_{i,t-j}(\theta), \\ \hat{B}_{\lambda_i}^\Omega(\theta) &= \hat{P}_{\alpha_i}(\theta) \sum_{j=0}^{\ell} T^{-1} \sum_{t=j+1}^T \hat{g}_{it}(\theta) \hat{g}_{it}(\theta)' \hat{P}_{\alpha_i}(\theta) \hat{g}_{i,t-j}(\theta), \\ \hat{B}_{\lambda_i}^W(\theta) &= \hat{P}_{\alpha_i}(\theta) \sum_{j=1}^{d_\alpha} \hat{\Omega}_{\alpha_{i,j}} [\hat{H}_{\alpha_{i,j}}^{W'}(\theta) - \hat{H}_{\alpha_{i,j}}'(\theta)], \end{aligned}$$

be estimators of  $\Sigma_{\alpha_i}$ ,  $H_{\alpha_i}$ ,  $P_{\alpha_i}$ ,  $\Sigma_{\alpha_i}^W$ ,  $H_{\alpha_i}^W$ ,  $J_{si}$ ,  $B_{si}^C$  and  $B_{si}^B$ . Let  $\hat{F}_{\alpha^{d_1}\theta^{d_2}i}(\theta, \hat{\alpha}_i(\theta))$  and  $F_{\alpha^{d_1}\theta^{d_2}i}(\theta, \alpha_i)$ , with  $F \in \{\Sigma, H, P, \Sigma^W, H^W, J_{si}, B_{si}^C, B_{si}^B\}$  denote their derivatives for  $0 \leq d_1 + d_2 \leq 1$ . Then,

$$\sqrt{T} \left( \hat{F}_{\alpha^{d_1}\theta^{d_2}i}(\bar{\theta}, \hat{\alpha}_i(\bar{\theta})) - F_{\alpha^{d_1}\theta^{d_2}i} \right) = o_{uP} \left( T^{1/10} \right).$$

where  $F_{\alpha^{d_1}\theta^{d_2}i} := F$  if  $d_1 + d_2 = 0$ .

*Proof.* The results follow by Theorem 3 and Lemma 6, using the algebraic properties of the  $o_{uP}$  orders and Lemma 12 of HK to show the properties of the estimators of the spectral expectations.  $\square$

**Lemma 10.** Assume that Conditions 1, 2, 3, 4, 5, and 6 hold. Then, for any  $\bar{\theta}$  between  $\hat{\theta}$  and  $\theta_0$ ,

$$\hat{J}_s(\bar{\theta}) = J_s + o_P(T^{-2/5}).$$

*Proof.* Note that

$$\sqrt{T} \left[ \hat{G}_{\theta_i}(\bar{\theta})' \hat{P}_{\alpha_i}(\bar{\theta}) \hat{G}_{\theta_i}(\bar{\theta}) - G'_{\theta_i} P_{\alpha_i} G_{\theta_i} \right] = o_{uP}(T^{1/10}),$$

by Theorem 3 and Lemmas 6 and 9, using the algebraic properties of the  $o_{uP}$  orders. The result then follows by a CLT for independent sequences since

$$\hat{J}_s(\bar{\theta}) - J_s = \hat{E}[\hat{G}_{\theta_i}(\bar{\theta})' \hat{P}_{\alpha_i}(\bar{\theta}) \hat{G}_{\theta_i}(\bar{\theta})] - \bar{E}[G'_{\theta_i} P_{\alpha_i} G_{\theta_i}] = n^{-1} \sum_{i=1}^n (G'_{\theta_i} P_{\alpha_i} G_{\theta_i} - \bar{E}[G'_{\theta_i} P_{\alpha_i} G_{\theta_i}]) + o_{uP}(T^{-2/5}).$$

$\square$

**Lemma 11.** Assume that Conditions 1, 2, 3, 4, 5, and 6 hold. Then, for any  $\bar{\theta}$  between  $\hat{\theta}$  and  $\theta_0$ ,

$$\hat{B}_s(\bar{\theta}) = B_s + o_P(T^{-2/5}).$$

*Proof.* Analogous to the proof of Lemma 10 replacing  $J_s$  by  $B_s$ .  $\square$

**Lemma 12.** Assume that Conditions 1, 2, 3, 4, 5, and 6 hold. Then, for any  $\bar{\theta}$  between  $\hat{\theta}$  and  $\theta_0$ , and  $\mathcal{B} = -J_s^{-1}B_s$ ,

$$\hat{\mathcal{B}}(\hat{\theta}) = -\hat{J}_s(\hat{\theta})^{-1} \hat{B}_s(\hat{\theta}) = \mathcal{B} + o_P(T^{-2/5}).$$

*Proof.* The result follows from Lemmas 10 and 11, using a Taylor expansion argument.  $\square$

## D.2. Proof of Theorem 5.

*Proof.* **Case I:  $\mathbf{C} = \mathbf{BC}$ .** By Lemmas 10 and 25

$$\sqrt{nT}(\hat{\theta} - \theta_0) = -\hat{J}_s(\bar{\theta})^{-1} \hat{s}(\theta_0) = -J_s^{-1} \hat{s}(\theta_0) + o_P(T^{-2/5}) O_P\left(\sqrt{\frac{n}{T}}\right) = -J_s^{-1} \hat{s}(\theta_0) + o_P(1).$$

Then, by Lemmas 12 and 25

$$\begin{aligned} \sqrt{nT}(\hat{\theta}^{BC} - \theta_0) &= \sqrt{nT}(\hat{\theta} - \theta_0) - \sqrt{nT} \frac{1}{T} \hat{\mathcal{B}}(\hat{\theta}) = -J_s^{-1} \hat{s}(\theta_0) + \sqrt{\frac{n}{T}} J_s^{-1} B_s + o_P(1) \\ &= -J_s^{-1} \left[ \frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_{si} + \sqrt{\frac{n}{T}} B_s - \sqrt{\frac{n}{T}} B_s \right] + o_P(1) \xrightarrow{d} N(0, J_s^{-1}). \end{aligned}$$

**Case II:  $\mathbf{C} = \mathbf{SBC}$ .** First, note that since the correction of the score is of order  $O_P(T^{-1})$ ,  $\hat{\theta}^{SBC} - \hat{\theta} = O_P(T^{-1})$ . Then, by a Taylor expansion of the corrected FOC around  $\hat{\theta}^{SBC} = \theta_0$

$$0 = \hat{s}(\hat{\theta}^{SBC}) - T^{-1} \hat{B}_s(\hat{\theta}^{SBC}) = \hat{s}(\theta_0) + \hat{J}_s(\bar{\theta})(\hat{\theta}^{SBC} - \theta_0) - T^{-1} B_s + o_P(T^{-2}),$$

where  $\bar{\theta}$  lies between  $\hat{\theta}^{SBC}$  and  $\theta_0$ . Then by Lemma 25

$$\begin{aligned}\sqrt{nT}(\hat{\theta}^{SBC} - \theta_0) &= -\hat{J}_s(\bar{\theta})^{-1} \left[ \sqrt{nT}\hat{s}(\theta_0) - n^{1/2}T^{-1/2}B_s \right] + o_P(1) \\ &= -\hat{J}_s(\bar{\theta})^{-1} \left[ \frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_{si} + \sqrt{\frac{n}{T}}B_s - \sqrt{\frac{n}{T}}B_s \right] + o_P(1) \xrightarrow{d} N(0, J_s^{-1}).\end{aligned}$$

**Case III:  $\mathbf{C} = \mathbf{IBC}$ .** A similar argument applies to the estimating equation (5.2), since  $\hat{\theta}^{IBC}$  is in a  $O(T^{-1})$  neighborhood of  $\theta_0$ .  $\square$

#### APPENDIX E. STOCHASTIC EXPANSION FOR $\tilde{\gamma}_{i0} = \tilde{\gamma}_i(\theta_0)$ AND $\hat{\gamma}_i = \hat{\gamma}_i(\theta_0)$

We characterize the stochastic expansions up to second order for one-step and two-step estimators of the individual effects given the true common parameter. We only provide detailed proofs of the results for the two-step estimator  $\hat{\gamma}_{i0}$ , because the proofs for the one-step estimator  $\tilde{\gamma}_{i0}$  follow by similar arguments. Lemmas 1 and 2 in the main text are corollaries of these expansions. The expressions for the scores and their derivatives in the components of the expansions are given in Appendix G.

**Lemma 13.** *Suppose that Conditions 1, 2, 3, and 4 hold. Then*

$$\sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}) = \tilde{\psi}_i^W + T^{-1/2}R_{1i}^W \xrightarrow{d} N(0, V_i^W),$$

where

$$\tilde{\psi}_i^W = \frac{1}{\sqrt{T}} \sum_{t=1}^T \psi_{it}^W = -(T_i^W)^{-1} \sqrt{T} \bar{t}_i^W = o_{uP}(T^{1/10}), \quad R_{1i}^W = o_{uP}(T^{1/5}), \quad V_i^W = E[\tilde{\psi}_i^W \tilde{\psi}_i^{W'}].$$

Also

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_i^W = O_P(1).$$

*Proof.* We just show the part of the remainder term because the rest of the proof is similar to the proof of Lemma 16. By the proof of Lemma 5,  $\sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}) = o_{uP}(T^{1/10})$  and

$$R_{1i}^W = - \underbrace{(T_i^W)^{-1}}_{=O_u(1)} \underbrace{(\hat{T}_i^W(\theta_0, \bar{\gamma}_{i0}) - T_i^W)}_{=o_{uP}(T^{1/10})} \underbrace{\sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0})}_{=o_{uP}(T^{1/10})} = o_{uP}(T^{1/5}).$$

$\square$

**Lemma 14.** *Suppose that Conditions 1, 2, 3, and 4 hold. Then,*

$$\sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}) = \tilde{\psi}_i^W + T^{-1/2}Q_{1i}^W + T^{-1}R_{2i}^W,$$

where

$$\begin{aligned}Q_{1i}^W &= -(T_i^W)^{-1} \left[ \tilde{A}_i^W \tilde{\psi}_i^W + \frac{1}{2} \sum_{j=1}^{d_g + d_\alpha} \tilde{\psi}_{i,j}^W T_{i,j}^W \tilde{\psi}_i^W \right] = o_{uP}(T^{1/5}), \\ \tilde{A}_i^W &= \sqrt{T}(\hat{T}_i^W - T_i^W) = o_{uP}(T^{1/10}), \quad R_{2i}^W = o_{uP}(T^{3/10}).\end{aligned}$$

Also,

$$\frac{1}{n} \sum_{i=1}^n Q_{1i}^W = O_P(1).$$

*Proof.* Similar to the proof of Lemma 18. □

**Lemma 15.** *Suppose that Conditions 1, 2, 3, and 4 hold. Then,*

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_i^W \xrightarrow{d} N(0, \bar{E}[V_i^W]), \quad \frac{1}{n} \sum_{i=1}^n Q_{1i}^W \xrightarrow{p} \bar{E}[B_{\gamma_i}^{W,I} + B_{\gamma_i}^{W,G} + B_{\gamma_i}^{W,1S}] =: B_{\gamma}^W,$$

where

$$\begin{aligned} V_i^W &= \begin{pmatrix} H_{\alpha_i}^W \\ P_{\alpha_i}^W \end{pmatrix} \Omega_i(H_{\alpha_i}^{W'}, P_{\alpha_i}^W), \\ B_{\gamma_i}^{W,I} &= \begin{pmatrix} B_{\lambda_i}^{W,I} \\ B_{\lambda_i}^{W,I} \end{pmatrix} = \begin{pmatrix} H_{\alpha_i}^W \\ P_{\alpha_i}^W \end{pmatrix} \left( \sum_{j=-\infty}^{\infty} E[G_{\alpha_i}(z_{it}) H_{\alpha_i}^W g(z_{i,t-j})] - \sum_{j=1}^{d_{\alpha}} G_{\alpha\alpha_i,j} H_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} / 2 \right), \\ B_{\gamma_i}^{W,G} &= \begin{pmatrix} B_{\lambda_i}^{W,G} \\ B_{\lambda_i}^{W,G} \end{pmatrix} = \begin{pmatrix} -\Sigma_{\alpha_i}^W \\ H_{\alpha_i}^{W'} \end{pmatrix} \sum_{j=-\infty}^{\infty} E[G_{\alpha_i}(z_{it})' P_{\alpha_i}^W g(z_{i,t-j})], \\ B_{\gamma_i}^{W,1S} &= \begin{pmatrix} B_{\lambda_i}^{W,1S} \\ B_{\lambda_i}^{W,1S} \end{pmatrix} = \begin{pmatrix} \Sigma_{\alpha_i}^W \\ -H_{\alpha_i}^{W'} \end{pmatrix} \left( \sum_{j=1}^{d_{\alpha}} G'_{\alpha\alpha_i,j} P_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} / 2 + \sum_{j=1}^{d_g} G'_{\alpha\alpha_i}(I_{d_{\alpha}} \otimes e_j) H_{\alpha_i}^W \Omega_i P_{\alpha_i,j}^W / 2 \right) \\ &\quad + \begin{pmatrix} H_{\alpha_i}^W \\ P_{\alpha_i}^W \end{pmatrix} \sum_{j=-\infty}^{\infty} E[\xi_i(z_{it}) P_{\alpha_i}^W g(z_{i,t-j})], \end{aligned}$$

for  $\Sigma_{\alpha_i}^W = (G'_{\alpha_i} W_i^{-1} G_{\alpha_i})^{-1}$ ,  $H_{\alpha_i}^W = \Sigma_{\alpha_i}^W G'_{\alpha_i} W_i^{-1}$ , and  $P_{\alpha_i}^W = W_i^{-1} - W_i^{-1} G_{\alpha_i} H_{\alpha_i}^W$ .

*Proof.* The results follow from Lemmas 13 and 14, noting that

$$\begin{aligned} (T_i^W)^{-1} &= - \begin{pmatrix} -\Sigma_{\alpha_i}^W & H_{\alpha_i}^W \\ H_{\alpha_i}^{W'} & P_{\alpha_i}^W \end{pmatrix}, \quad \psi_{it}^W = - \begin{pmatrix} H_{\alpha_i}^W \\ P_{\alpha_i}^W \end{pmatrix} g(z_{it}), \\ E[\tilde{\psi}_i^W \tilde{\psi}_i^{W'}] &= \begin{pmatrix} H_{\alpha_i}^W \\ P_{\alpha_i}^W \end{pmatrix} \Omega_i(H_{\alpha_i}^{W'}, P_{\alpha_i}^W), \\ E[\tilde{A}_i^W \tilde{\psi}_i^W] &= \sum_{j=-\infty}^{\infty} \begin{pmatrix} E[G_{\alpha_i}(z_{it})' P_{\alpha_i}^W g(z_{i,t-j})] \\ E[G_{\alpha_i}(z_{it})' H_{\alpha_i}^W g(z_{i,t-j})] + E[\xi_i(z_{it}) P_{\alpha_i}^W g(z_{i,t-j})] \end{pmatrix}, \\ E[\tilde{\psi}_{i,j}^W T_{i,j}^W \tilde{\psi}_i^W] &= \begin{cases} - \begin{pmatrix} G'_{\alpha\alpha_i,j} P_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} \\ G'_{\alpha\alpha_i,j} H_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} \end{pmatrix}, & \text{if } j \leq d_{\alpha}; \\ G'_{\alpha\alpha_i}(I_{d_{\alpha}} \otimes e_{j-d_{\alpha}}) H_{\alpha_i}^W \Omega_i P_{\alpha_i,j}^W, & \text{if } j > d_{\alpha}. \end{cases} \end{aligned}$$

□

**Lemma 16.** *Suppose that Conditions 1, 2, 3, 4, 5, and 6 hold. Then,*

$$\sqrt{T}(\hat{\gamma}_{i0} - \gamma_{i0}) = \tilde{\psi}_i + T^{-1/2} R_{1i} \xrightarrow{d} N(0, V_i),$$

where

$$\tilde{\psi}_i = \frac{1}{\sqrt{T}} \sum_{t=1}^T \psi_{it} = -(T_i^{\Omega})^{-1} \sqrt{T} t_i^{\Omega} = o_{uP}(T^{1/10}), \quad R_{1i} = o_{uP}(T^{1/5}), \quad V_i = E[\tilde{\psi}_i \tilde{\psi}_i'].$$

Also

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_i = O_P(1)$$



*Proof.* The statements about  $\tilde{\psi}_i$  follow by the proof of Lemma 5 applied to the second stage, and the CLT in Lemma 3 of HK. From a similar argument to the proof of Lemma 5,

$$\begin{aligned} R_{1i} &= \underbrace{-(T_i^\Omega)^{-1}}_{=O_u(1)} \underbrace{\sqrt{T}(\hat{T}_i^\Omega(\theta_0, \bar{\gamma}_i) - T_i^\Omega)}_{=o_{uP}(T^{1/10})} \underbrace{\sqrt{T}(\hat{\gamma}_{i0} - \gamma_{i0})}_{=o_{uP}(T^{1/10})} - \underbrace{(T_i^\Omega)^{-1}}_{=O_u(1)} \underbrace{\sqrt{T}(\hat{T}_i^R(\theta_0, \bar{\gamma}_i) - T_i^R)}_{=o_{uP}(T^{1/10})} \underbrace{\sqrt{T}(\hat{\gamma}_{i0} - \gamma_{i0})}_{=o_{uP}(T^{1/10})} \\ &= o_{uP}(T^{1/5}), \end{aligned}$$

by Conditions 3 and 4.  $\square$

**Lemma 17.** *Assume that Conditions 1, 2, 3, 4 and 5 hold. Then,*

$$\hat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) = \Omega_i + T^{-1/2} \tilde{\psi}_{\Omega i}^W + T^{-1} R_{1\Omega i}^W,$$

where

$$\tilde{\psi}_{\Omega i}^W = \sqrt{T} \left( \hat{\Omega}_i - \Omega_i \right) + \sum_{j=1}^{d_\alpha} \Omega_{\alpha_{i,j}} \tilde{\psi}_{i,j}^W = o_{up}(T^{1/10}), \quad R_{1\Omega i}^W = o_{up}(T^{1/5}),$$

and  $\tilde{\psi}_{i,j}^W$  is the  $j$ th element of  $\tilde{\psi}_{i,j}^W$ .

*Proof.* By a mean value expansion around  $(\theta_0, \alpha_{i0})$ ,

$$\hat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) = \hat{\Omega}_i + \sum_{j=1}^{d_\alpha} \hat{\Omega}_{\alpha_{i,j}}(\bar{\theta}, \bar{\alpha}_i)(\tilde{\alpha}_{i,j} - \alpha_{i0,j}) + \sum_{j=1}^{d_\theta} \hat{\Omega}_{\theta_j}(\bar{\theta}, \bar{\alpha}_i)(\tilde{\theta}_j - \theta_{0,j}),$$

where  $(\bar{\theta}, \bar{\alpha}_i)$  lies between  $(\tilde{\theta}, \tilde{\alpha}_i)$  and  $(\theta_0, \alpha_{i0})$ . The expressions for  $\tilde{\psi}_{\Omega i}^W$  can be obtained using the expansions for  $\tilde{\gamma}_{i0}$  in Lemma 13 since  $\tilde{\gamma}_i - \tilde{\gamma}_{i0} = o_{uP}(T^{-3/10})$ . The order of this term follows from Lemma 13 and the CLT for independent sequences. The remainder term is

$$R_{1\Omega i}^W = \sum_{j=1}^{d_\alpha} \left[ \Omega_{\alpha_{i,j}} R_{1i,j}^W + \sqrt{T}(\hat{\Omega}_{\alpha_{i,j}}(\bar{\theta}, \bar{\alpha}_i) - \Omega_{\alpha_{i,j}}) \sqrt{T}(\tilde{\alpha}_{i,j} - \alpha_{i0,j}) \right] + \sum_{j=1}^{d_\theta} \hat{\Omega}_{\theta_j}(\bar{\theta}, \bar{\alpha}_i) T(\tilde{\theta}_j - \theta_{0,j}).$$

The uniform rate of convergence then follows by Lemmas 8 and 13, and Theorem 1.  $\square$

**Lemma 18.** *Suppose that Conditions 1, 2, 3, 4, and 5 hold. Then,*

$$(E.1) \quad \sqrt{T}(\hat{\gamma}_{i0} - \gamma_{i0}) = \tilde{\psi}_i + T^{-1/2} Q_{1i} + T^{-1} R_{2i},$$

where

$$\begin{aligned} Q_{1i}(\tilde{\psi}_i, \tilde{\alpha}_i) &= -(T_i^\Omega)^{-1} \left[ \tilde{A}_i^\Omega \tilde{\psi}_i + \frac{1}{2} \sum_{j=1}^{d_g+d_\alpha} \tilde{\psi}_{i,j} T_{i,j}^\Omega \tilde{\psi}_i + \text{diag}[0, \tilde{\psi}_{\Omega i}^W] \tilde{\psi}_i \right] = o_{uP}(T^{1/5}), \\ \tilde{A}_i^\Omega &= \sqrt{T}(\hat{T}_i^\Omega - T_i^\Omega) = o_{uP}(T^{1/10}), \quad R_{2i} = o_{uP}(T^{3/10}). \end{aligned}$$

Also,

$$\frac{1}{n} \sum_{i=1}^n Q_{1i} = O_P(1).$$

*Proof.* By a second order Taylor expansion of the FOC for  $\hat{\gamma}_{i0}$ , we have

$$0 = \hat{t}_i(\theta_0, \hat{\gamma}_{i0}) = \hat{t}_i^\Omega + \hat{T}_i(\hat{\gamma}_{i0} - \gamma_{i0}) + \frac{1}{2} \sum_{j=1}^{d_g+d_\alpha} (\hat{\gamma}_{i0,j} - \gamma_{i0,j}) \hat{T}_{i,j}(\theta_0, \bar{\gamma}_i)(\hat{\gamma}_{i0} - \gamma_{i0}),$$

where  $\bar{\gamma}_i$  is between  $\hat{\gamma}_{i0}$  and  $\gamma_{i0}$ . The expression for  $Q_{1i}$  can be obtained in a similar fashion as in Lemma A4 in Newey and Smith (2004). The rest of the properties for  $Q_{1i}$  follow by Lemma 5 applied to the second stage, Lemma 16, and an argument similar to the proof of Theorem 1 in HK that uses Corollary A.2 of Hall and Heide (1980, p. 278) and Lemma 1 of Andrews (1991). The remainder term is

$$\begin{aligned} R_{2i} &= -(T_i^\Omega)^{-1} \left[ \tilde{A}_i^\Omega R_{1i} + \sum_{j=1}^{d_g+d_\alpha} \left[ R_{1i,j} T_{i,j}^\Omega \sqrt{T}(\hat{\gamma}_{i0} - \gamma_{i0}) + \tilde{\psi}_{i,j} T_{i,j}^\Omega R_{1i} \right] / 2 \right] \\ &\quad - (T_i^\Omega)^{-1} \sum_{j=1}^{d_g+d_\alpha} \sqrt{T}(\hat{\gamma}_{i0,j} - \gamma_{i0,j}) \sqrt{T}(\hat{T}_{i,j}^\Omega(\theta_0, \bar{\gamma}_i) - T_{i,j}^\Omega) \sqrt{T}(\hat{\gamma}_{i0} - \gamma_{i0}) / 2 \\ &\quad - (T_i^\Omega)^{-1} \left[ \text{diag}[0, R_{1\Omega_i}^W] \sqrt{T}(\hat{\gamma}_{i0} - \gamma_{i0}) + \text{diag}[0, \tilde{\psi}_{\Omega_i}^W] R_{1i} \right]. \end{aligned}$$

The uniform rate of convergence then follows by Lemmas 5 and 16, and Conditions 3 and 4.  $\square$

**Lemma 19.** *Suppose that Conditions 1, 2, 3, 4, 5, and 6 hold. Then,*

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_i \xrightarrow{d} N(0, \bar{E}[V_i]), \quad \frac{1}{n} \sum_{i=1}^n Q_{1i} \xrightarrow{p} \bar{E}[B_{\gamma_i}^I + B_{\gamma_i}^G + B_{\gamma_i}^\Omega + B_{\gamma_i}^W] =: B_\gamma,$$

where

$$\begin{aligned} V_i &= \text{diag}(\Sigma_{\alpha_i}, P_{\alpha_i}), \\ B_{\gamma_i}^I &= \begin{pmatrix} B_{\alpha_i}^I \\ B_{\lambda_i}^I \end{pmatrix} = \begin{pmatrix} H_{\alpha_i} \\ P_{\alpha_i} \end{pmatrix} \left( - \sum_{j=1}^{d_\alpha} G_{\alpha\alpha_i,j} \Sigma_{\alpha_i} / 2 + E[G_{\alpha_i}(z_{it}) H_{\alpha_i} g(z_{i,t-j})] \right), \\ B_{\gamma_i}^G &= \begin{pmatrix} B_{\alpha_i}^G \\ B_{\lambda_i}^G \end{pmatrix} = \begin{pmatrix} -\Sigma_{\alpha_i} \\ H_{\alpha_i}' \end{pmatrix} \sum_{j=0}^{\infty} E[G_{\alpha_i}(z_{it})' P_{\alpha_i} g(z_{i,t-j})], \\ B_{\gamma_i}^\Omega &= \begin{pmatrix} B_{\alpha_i}^\Omega \\ B_{\lambda_i}^\Omega \end{pmatrix} = \begin{pmatrix} H_{\alpha_i} \\ P_{\alpha_i} \end{pmatrix} \sum_{j=0}^{\infty} E[g(z_{it}) g(z_{it})' P_{\alpha_i} g(z_{i,t-j})], \\ B_{\gamma_i}^W &= \begin{pmatrix} B_{\alpha_i}^W \\ B_{\lambda_i}^W \end{pmatrix} = \begin{pmatrix} H_{\alpha_i} \\ P_{\alpha_i} \end{pmatrix} \sum_{j=1}^{d_\alpha} \Omega_{\alpha_i,j} (H_{\alpha_i,j}^{W'} - H_{\alpha_i,j}'), \end{aligned}$$

for  $\Sigma_{\alpha_i} = (G_{\alpha_i}' \Omega_i^{-1} G_{\alpha_i})^{-1}$ ,  $H_{\alpha_i} = \Sigma_{\alpha_i} G_{\alpha_i}' \Omega_i^{-1}$ , and  $P_{\alpha_i} = \Omega_i^{-1} - \Omega_i^{-1} G_{\alpha_i} H_{\alpha_i}$ .

*Proof.* The results follow by Lemmas 16 and 18, noting that

$$\begin{aligned} (T_i^\Omega)^{-1} &= - \begin{pmatrix} -\Sigma_{\alpha_i} & H_{\alpha_i} \\ H_{\alpha_i}' & P_{\alpha_i} \end{pmatrix}, \quad \psi_{it} = - \begin{pmatrix} H_{\alpha_i} \\ P_{\alpha_i} \end{pmatrix} g(z_{it}), \\ E[\tilde{\psi}_i \tilde{\psi}_i'] &= \begin{pmatrix} \Sigma_{\alpha_i} & 0 \\ 0 & P_{\alpha_i} \end{pmatrix}, \quad E[\tilde{A}_i^\Omega \tilde{\psi}_i] = \sum_{j=0}^{\infty} \begin{pmatrix} E[G_{\alpha_i}(z_{it})' P_{\alpha_i} g(z_{i,t-j})] \\ E[G_{\alpha_i}(z_{it})' H_{\alpha_i} g(z_{i,t-j})] \end{pmatrix}, \\ E[\tilde{\psi}_{i,j} T_{i,j}^\Omega \tilde{\psi}_i] &= \begin{cases} - \begin{pmatrix} 0 \\ G_{\alpha\alpha_i,j}' \Sigma_{\alpha_i} \end{pmatrix}, & \text{if } j \leq d_\alpha; \\ 0, & \text{if } j > d_\alpha. \end{cases} \\ E[\text{diag}[0, \tilde{\psi}_{\Omega_i}^W] \tilde{\psi}_i] &= \begin{pmatrix} 0 \\ \sum_{j=0}^{\infty} E[g(z_{it}) g(z_{it})' P_{\alpha_i} g(z_{i,t-j})] + \sum_{j=1}^{d_\alpha} \Omega_{\alpha_i,j} (H_{\alpha_i,j}^{W'} - H_{\alpha_i,j}) \end{pmatrix}. \end{aligned}$$

$\square$

APPENDIX F. STOCHASTIC EXPANSION FOR  $\hat{s}_i^W(\theta_0, \tilde{\gamma}_{i0})$  AND  $\hat{s}_i(\theta_0, \hat{\gamma}_{i0})$

We characterize stochastic expansions up to second order for one-step and two-step profile scores of the common parameter evaluated at the true value of the common parameter. The expressions for the scores and their derivatives in the components of the expansions are given in Appendix G.

**Lemma 20.** *Suppose that Conditions 1, 2, 3, and 4 hold. Then,*

$$\hat{s}_i^W(\theta_0, \tilde{\gamma}_{i0}) = T^{-1/2} \tilde{\psi}_{si}^W + T^{-1} Q_{1si}^W + T^{-3/2} R_{2si}^W,$$

where

$$\begin{aligned} \tilde{\psi}_{si}^W &= M_i^W \tilde{\psi}_i^W = o_{uP}(T^{1/10}), \quad Q_{1si}^W = M_i^W Q_{1i}^W + \tilde{C}_i^W \tilde{\psi}_i^W + \frac{1}{2} \sum_{j=1}^{d_g+d_\alpha} \tilde{\psi}_{i,j}^W M_{i,j}^W \tilde{\psi}_i^W = o_{uP}(T^{1/5}), \\ \tilde{C}_i^W &= \sqrt{T}(\widehat{M}_i^W - M_i^W) = o_{uP}(T^{1/10}), \quad R_{2si}^W = o_{uP}(T^{2/5}). \end{aligned}$$

Also,

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_{si}^W = O_P(1), \quad \frac{1}{n} \sum_{i=1}^n Q_{1si}^W = O_P(1).$$

*Proof.* By a second order Taylor expansion of  $\hat{s}_i^W(\theta_0, \tilde{\gamma}_{i0})$  around  $\tilde{\gamma}_{i0} = \gamma_{i0}$ ,

$$\hat{s}_i^W(\theta_0, \tilde{\gamma}_{i0}) = \hat{s}_i^W + \widehat{M}_i^W(\tilde{\gamma}_{i0} - \gamma_{i0}) + \frac{1}{2} \sum_{j=1}^{d_g+d_\alpha} (\tilde{\gamma}_{i0,j} - \gamma_{i0,j}) \widehat{M}_{i,j}^W(\theta_0, \bar{\gamma}_i)(\tilde{\gamma}_{i0} - \gamma_{i0}),$$

where  $\bar{\gamma}_i$  is between  $\tilde{\gamma}_{i0}$  and  $\gamma_{i0}$ . Noting that  $\hat{s}_i^W(\theta_0, \gamma_{i0}) = 0$  and using the expansion for  $\tilde{\gamma}_{i0}$  in Lemma 14, we can obtain the expressions for  $\tilde{\psi}_{si}^W$  and  $Q_{1si}^W$ , after some algebra. The rest of the properties for these terms follow by the properties of  $\tilde{\psi}_i^W$  and  $Q_{1i}^W$ . The remainder term is

$$\begin{aligned} R_{2si}^W &= M_i^W R_{2i}^W + \tilde{C}_i^W R_{1i}^W + \frac{1}{2} \sum_{j=1}^{d_g+d_\alpha} \left[ R_{1i,j}^W M_{i,j}^W \sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}) + \tilde{\psi}_{i,j}^W M_{i,j}^W R_{1i}^W \right] \\ &+ \frac{1}{2} \sum_{j=1}^{d_g+d_\alpha} \sqrt{T}(\tilde{\gamma}_{i0,j} - \gamma_{i0,j}) \sqrt{T}(\widehat{M}_{i,j}^W(\theta_0, \bar{\gamma}_i) - M_{i,j}^W) \sqrt{T}(\tilde{\gamma}_{i0} - \gamma_{i0}). \end{aligned}$$

The uniform order of  $R_{2si}^W$  follows by the properties of the components in the expansion of  $\tilde{\gamma}_{i0}$ , Lemma 5, and Conditions 3 and 4.  $\square$

**Lemma 21.** *Suppose that Conditions 1, 2, 3, and 4 hold. We then have*

$$\begin{aligned} \frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_{si}^W &\xrightarrow{d} N(0, V_s^W), \quad V_s^W = \bar{E}[G'_{\theta_i} P_{\alpha_i}^W \Omega_i P_{\alpha_i}^W G_{\theta_i}], \\ \frac{1}{n} \sum_{i=1}^n Q_{1si}^W &\xrightarrow{p} \bar{E}E[Q_{1si}^W] = \bar{E}[B_{si}^{W,B} + B_{si}^{W,C} + B_{si}^{W,V}] =: B_s^W, \end{aligned}$$

where  $B_{si}^{W,B} = -G'_{\theta_i} B_{\lambda_i}^W = -G'_{\theta_i} (B_{\lambda_i}^{W,I} + B_{\lambda_i}^{W,G} + B_{\lambda_i}^{W,1S})$ ,  $B_{si}^{W,C} = \sum_{j=-\infty}^{\infty} E[G_{\theta_i}(z_{it})' P_{\alpha_i}^W g(z_{i,t-j})]$ ,  $B_{si}^{W,V} = -\sum_{j=1}^{d_\alpha} G'_{\theta_{\alpha_i,j}} P_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} / 2 - \sum_{j=1}^{d_g} G'_{\theta_{\alpha_i}} (Id_\alpha \otimes e_j) H_{\alpha_i}^W \Omega_i P_{\alpha_i,j}^W / 2$ ,  $H_{\alpha_i}^W = \Sigma_{\alpha_i}^W G'_{\alpha_i} W_i^{-1}$ ,  $\Sigma_{\alpha_i}^W = (G'_{\alpha_i} W_i^{-1} G_{\alpha_i})^{-1}$ , and  $P_{\alpha_i}^W = W_i^{-1} - W_i^{-1} G_{\alpha_i} H_{\alpha_i}^W$ .

*Proof.* The results follow by Lemmas 20 and 15, noting that

$$\begin{aligned} E \left[ \tilde{\psi}_{si}^W \tilde{\psi}_{si}^{W'} \right] &= M_i^W \begin{pmatrix} H_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} & H_{\alpha_i}^W \Omega_i P_{\alpha_i}^W \\ P_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'} & P_{\alpha_i}^W \Omega_i P_{\alpha_i}^W \end{pmatrix} M_i^{W'}, \\ E \left[ \tilde{C}_i^W \tilde{\psi}_i^W \right] &= \sum_{j=-\infty}^{\infty} E \left[ G_{\theta_i}(z_{it})' P_{\alpha_i}^W g(z_{i,t-j}) \right], \\ E \left[ \tilde{\psi}_{i,j}^W M_{i,j}^W \tilde{\psi}_i^W \right] &= \begin{cases} -G'_{\theta_{\alpha_i,j}} P_{\alpha_i}^W \Omega_i H_{\alpha_i}^{W'}, & \text{if } j \leq d_{\alpha}; \\ -G'_{\theta_{\alpha_i}} (I_{d_{\alpha}} \otimes e_{j-d_{\alpha}}) H_{\alpha_i}^W \Omega_i P_{\alpha_i,j}^W, & \text{if } j > d_{\alpha}. \end{cases} \end{aligned}$$

□

**Lemma 22.** Suppose that Conditions 1, 2, 3, and 4 hold. Then, for  $\hat{s}^W(\theta_0) = n^{-1} \sum_{i=1}^n \hat{s}_i^W(\theta_0, \tilde{\gamma}_{i0})$ ,

$$\sqrt{nT} \hat{s}^W(\theta_0) \xrightarrow{d} N(\kappa B_s^W, V_s^W),$$

where  $B_s^W$  and  $V_s^W$  are defined in Lemma 21.

*Proof.* By Lemma 20,

$$\begin{aligned} \sqrt{nT} \hat{s}^W(\theta_0) &= \underbrace{\frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_{si}^W}_{=O_P(1)} + \underbrace{\sqrt{\frac{n}{T}} \frac{1}{n} \sum_{i=1}^n Q_{1si}^W}_{=O_P(1)} + \underbrace{\sqrt{\frac{n}{T^2}} \frac{1}{n} \sum_{i=1}^n R_{2si}^W}_{=o_P(1)} \\ &= \frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_{si}^W + \sqrt{\frac{n}{T}} \frac{1}{n} \sum_{i=1}^n Q_{1si}^W + o_P(1). \end{aligned}$$

Then, the result follows by Lemma 21. □

**Lemma 23.** Suppose that Conditions 1, 2, 3, 4, 5, and 6 hold. Then,

$$\hat{s}_i(\theta_0, \tilde{\gamma}_{i0}) = T^{-1/2} \tilde{\psi}_{si} + T^{-1} Q_{1si} + T^{-3/2} R_{2si},$$

where all the terms are identical to that of Lemma 20 after replacing  $W$  by  $\Omega$ . Also, the properties of all the terms of the expansion are the analogous to those of Lemma 20.

*Proof.* The proof is similar to the proof of Lemma 20. □

**Lemma 24.** Suppose that Conditions 1, 2, 3, 4, 5, and 6 hold. Then,

$$\begin{aligned} \frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\psi}_{si} &\xrightarrow{d} N(0, J_s), \quad J_s = \bar{E}[G'_{\theta_i} P_{\alpha_i} G_{\theta_i}] \\ \frac{1}{n} \sum_{i=1}^n Q_{1si} &\xrightarrow{p} \bar{E}E[Q_{1si}] = \bar{E}[B_{si}^B + B_{si}^C] =: B_s, \end{aligned}$$

where  $B_{si}^B = -G'_{\theta_i} (B_{\lambda_i}^I + B_{\lambda_i}^G + B_{\lambda_i}^{\Omega} + B_{\lambda_i}^W)$ ,  $B_{si}^C = \sum_{j=0}^{\infty} E[G_{\theta_i}(z_{it})' P_{\alpha_i} g(z_{i,t-j})]$ ,  $P_{\alpha_i} = \Omega_i^{-1} - \Omega_i^{-1} G_{\alpha_i} H_{\alpha_i}$ ,  $H_{\alpha_i} = \Sigma_{\alpha_i} G'_{\alpha_i} \Omega_i^{-1}$ , and  $\Sigma_{\alpha_i} = (G'_{\alpha_i} \Omega_i^{-1} G_{\alpha_i})^{-1}$ .

*Proof.* The results follow by Lemmas 16, 18, 19 and 23, noting that

$$E \left[ \tilde{\psi}_{si} \tilde{\psi}_{si}' \right] = M_i^{\Omega} \begin{pmatrix} \Sigma_{\alpha_i} & 0 \\ 0 & P_{\alpha_i} \end{pmatrix} M_i^{\Omega'}, \quad E \left[ \tilde{C}_i^{\Omega} \tilde{\psi}_i \right] = \sum_{j=0}^{\infty} E \left[ G_{\theta_i}(z_{it})' P_{\alpha_i} g(z_{i,t-j}) \right], \quad E \left[ \tilde{\psi}_{i,j} M_{i,j}^{\Omega} \tilde{\psi}_i \right] = 0.$$

□

**Lemma 25.** Suppose that Conditions 1, 2, 3, 5, and 4 hold. Then, or  $\widehat{s}(\theta_0) = n^{-1} \sum_{i=1}^n \widehat{s}_i(\theta_0, \widehat{\gamma}_{i0})$ ,

$$\sqrt{nT}\widehat{s}(\theta_0) = \frac{1}{\sqrt{n}} \sum_{i=1}^n \widetilde{\psi}_{si} + \sqrt{\frac{n}{T}} B_s + o_P(1) \xrightarrow{d} N(\kappa B_s, J_s),$$

where  $\widetilde{\psi}_{si}$  and  $B_s$  are defined in Lemmas 23 and 24, respectively.

*Proof.* Using the expansion form obtained in Lemma 23, we can get the result by examining each term with Lemma 24.  $\square$

## APPENDIX G. SCORES AND DERIVATIVES

**G.1. One-Step Score and Derivatives: Individual Effects.** We denote dimensions of  $g(z_{it})$ ,  $\alpha_i$ , and  $\theta$  by  $d_g$ ,  $d_\alpha$  and  $d_\theta$ . The symbol  $\otimes$  denotes kronecker product of matrices, and  $I_{d_\alpha}$  denotes a  $d_\alpha$ -order identity matrix. Let  $G_{\alpha\alpha_i}(z_{it}; \theta, \alpha_i) := (G_{\alpha\alpha_{i,1}}(z_{it}; \theta, \alpha_i)', \dots, G_{\alpha\alpha_{i,d_\alpha}}(z_{it}; \theta, \alpha_i)')'$ , where

$$G_{\alpha\alpha_{i,j}}(z_{it}; \theta, \alpha_i) = \frac{\partial G_{\alpha_i}(z_{it}; \theta, \alpha_i)}{\partial \alpha_{i,j}}.$$

We denote derivatives of  $G_{\alpha\alpha_i}(z_{it}; \theta, \alpha_i)$  with respect to  $\alpha_{i,j}$  by  $G_{\alpha\alpha, \alpha_{i,j}}(z_{it}; \theta, \alpha_i)$ , and use additional subscripts for higher order derivatives.

G.1.1. *Score.*

$$\widehat{t}_i^W(\theta, \gamma_i) = -\frac{1}{T} \sum_{t=1}^T \begin{pmatrix} G_{\alpha_i}(z_{it}; \theta, \alpha_i)' \lambda_i \\ g(z_{it}; \theta, \alpha_i) + \widehat{W}_i \lambda_i \end{pmatrix} = - \begin{pmatrix} \widehat{G}_{\alpha_i}(\theta, \alpha_i)' \lambda_i \\ \widehat{g}_i(\theta, \alpha_i) + \widehat{W}_i \lambda_i \end{pmatrix}.$$

G.1.2. *Derivatives with respect to the fixed effects.*

**First Derivatives**

$$\begin{aligned} \widehat{T}_i^W(\theta, \gamma_i) &= \frac{\partial \widehat{t}_i^W(\gamma_i, \theta)}{\partial \gamma_i'} = - \begin{pmatrix} \widehat{G}_{\alpha\alpha_i}(\theta, \alpha_i)'(I_{d_\alpha} \otimes \lambda_i) & \widehat{G}_{\alpha_i}(\theta, \alpha_i)' \\ \widehat{G}_{\alpha_i}(\theta, \alpha_i) & \widehat{W}_i \end{pmatrix}. \\ T_i^W &= E[\widehat{T}_i^W] = - \begin{pmatrix} 0 & G'_{\alpha_i} \\ G_{\alpha_i} & W_i \end{pmatrix}. \\ (T_i^W)^{-1} &= - \begin{pmatrix} -\Sigma_{\alpha_i}^W & H_{\alpha_i}^W \\ H_{\alpha_i}^{W'} & P_{\alpha_i}^W \end{pmatrix}. \end{aligned}$$

**Second Derivatives**

$$\begin{aligned} \widehat{T}_{i,j}^W(\theta, \gamma_i) &= \frac{\partial^2 \widehat{t}_i^W(\theta, \gamma_i)}{\partial \gamma_{i,j} \partial \gamma_i'} = \begin{cases} - \begin{pmatrix} \widehat{G}_{\alpha\alpha, \alpha_{i,j}}(\theta, \alpha_i)'(I_{d_\alpha} \otimes \lambda_i) & \widehat{G}_{\alpha\alpha_{i,j}}(\theta, \alpha_i)' \\ \widehat{G}_{\alpha\alpha_{i,j}}(\theta, \alpha_i) & 0 \end{pmatrix}, & \text{if } j \leq d_\alpha; \\ - \begin{pmatrix} \widehat{G}_{\alpha\alpha_i}(\theta, \alpha_i)'(I_{d_\alpha} \otimes e_{j-d_\alpha}) & 0 \\ 0 & 0 \end{pmatrix}, & \text{if } j > d_\alpha. \end{cases} \\ T_{i,j}^W &= E[\widehat{T}_{i,j}^W(\gamma_{i0}; \theta_0)] = \begin{cases} - \begin{pmatrix} 0 & G'_{\alpha\alpha_{i,j}} \\ G_{\alpha\alpha_{i,j}} & 0 \end{pmatrix}, & \text{if } j \leq d_\alpha; \\ - \begin{pmatrix} G'_{\alpha\alpha_i}(I_{d_\alpha} \otimes e_{j-d_\alpha}) & 0 \\ 0 & 0 \end{pmatrix}, & \text{if } j > d_\alpha. \end{cases} \end{aligned}$$

### Third Derivatives

$$\hat{T}_{i,jk}^W(\theta, \gamma_i) = \frac{\partial^3 \hat{t}_i^W(\theta, \gamma_i)}{\partial \gamma_{i,k} \partial \gamma_{i,j} \partial \gamma_i'} = \begin{cases} - \begin{pmatrix} \hat{G}_{\alpha\alpha, \alpha\alpha_{i,jk}}(\theta, \alpha_i)'(I_{d_\alpha} \otimes \lambda_i) & \hat{G}_{\alpha\alpha\alpha_{i,jk}}(\theta, \alpha_i)' \\ \hat{G}_{\alpha\alpha\alpha_{i,jk}}(\theta, \alpha_i) & 0 \end{pmatrix}, & \text{if } j \leq d_\alpha, k \leq d_\alpha; \\ - \begin{pmatrix} \hat{G}_{\alpha\alpha, \alpha_{i,j}}(\theta, \alpha_i)'(I_{d_\alpha} \otimes e_{k-d_\alpha}) & 0 \\ 0 & 0 \end{pmatrix}, & \text{if } j \leq d_\alpha, k > d_\alpha; \\ - \begin{pmatrix} \hat{G}_{\alpha\alpha, \alpha_{i,k}}(\theta, \alpha_i)'(I_{d_\alpha} \otimes e_{j-d_\alpha}) & 0 \\ 0 & 0 \end{pmatrix}, & \text{if } j > d_\alpha, k \leq d_\alpha; \\ \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}, & \text{if } j > d_\alpha, k > d_\alpha. \end{cases}$$

$$T_{i,jk}^W = E[\hat{T}_{i,jk}^W] = \begin{cases} - \begin{pmatrix} 0 & G'_{\alpha\alpha\alpha_{i,jk}} \\ G_{\alpha\alpha\alpha_{i,jk}} & 0 \end{pmatrix}, & \text{if } j \leq d_\alpha, k \leq d_\alpha; \\ - \begin{pmatrix} G'_{\alpha\alpha, \alpha_{i,j}}(I_{d_\alpha} \otimes e_{k-d_\alpha}) & 0 \\ 0 & 0 \end{pmatrix}, & \text{if } j \leq d_\alpha, k > d_\alpha; \\ - \begin{pmatrix} G'_{\alpha\alpha, \alpha_{i,k}}(I_{d_\alpha} \otimes e_{j-d_\alpha}) & 0 \\ 0 & 0 \end{pmatrix}, & \text{if } j > d_\alpha, k \leq d_\alpha; \\ \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}, & \text{if } j > d_\alpha, k > d_\alpha. \end{cases}$$

G.1.3. *Derivatives with respect to the common parameter.*

#### First Derivatives

$$\hat{N}_{i,j}^W(\theta, \gamma_i) = \frac{\partial \hat{t}_i^W(\gamma_i, \theta)}{\partial \theta_j} = - \begin{pmatrix} \hat{G}_{\theta_j \alpha_i}(\theta, \alpha_i)' \lambda_i \\ \hat{G}_{\theta_{i,j}}(\theta, \alpha_i) \end{pmatrix}.$$

$$N_{i,j}^W = E[\hat{N}_{i,j}^W] = - \begin{pmatrix} 0 \\ G_{\theta_{i,j}} \end{pmatrix}.$$

**G.2. One-Step Score and Derivatives: Common Parameters.** Let  $G_{\theta\alpha_i}(z_{it}; \theta, \alpha_i) := (G_{\theta\alpha_{i,1}}(z_{it}; \theta, \alpha_i)', \dots, G_{\theta\alpha_{i,d_\alpha}}(z_{it}; \theta, \alpha_i)')'$ , where

$$G_{\theta\alpha_{i,j}}(z_{it}; \theta, \alpha_i) = \frac{\partial G_\theta(z_{it}; \theta, \alpha_i)}{\partial \alpha_{i,j}}.$$

We denote the derivatives of  $G_{\theta\alpha_i}(z_{it}; \theta, \alpha_i)$  with respect to  $\alpha_{i,j}$  by  $G_{\theta\alpha, \alpha_{i,j}}(z_{it}; \theta, \alpha_i)$ , and use additional subscripts for higher order derivatives.

G.2.1. *Score.*

$$\hat{s}_i^W(\theta, \gamma_i) = -\frac{1}{T} \sum_{t=1}^T G_\theta(z_{it}; \theta, \alpha_i)' \lambda_i = -\hat{G}_{\theta_i}(\theta, \alpha_i)' \lambda_i.$$

G.2.2. *Derivatives with respect to the fixed effects.*

#### First Derivatives

$$\begin{aligned}\widehat{M}_i^W(\theta, \gamma_i) &= \frac{\partial \widehat{s}_i^W(\theta, \gamma_i)}{\partial \gamma_i'} = - \begin{pmatrix} \widehat{G}_{\theta\alpha_i}(\theta, \alpha_i)'(I_{d_\alpha} \otimes \lambda_i) & \widehat{G}_{\theta_i}(\theta, \alpha_i)' \end{pmatrix}. \\ M_i^W &= E \left[ \widehat{M}_i^W \right] = - \begin{pmatrix} 0 & G'_{\theta_i} \end{pmatrix}.\end{aligned}$$

## Second Derivatives

$$\begin{aligned}\widehat{M}_{i,j}^W(\theta, \gamma_i) &= \frac{\partial^2 \widehat{s}_i^W(\theta, \gamma_i)}{\partial \gamma_{i,j} \partial \gamma_i'} = \begin{cases} - \begin{pmatrix} \widehat{G}_{\theta\alpha, \alpha_{i,j}}(\theta, \alpha_i)'(I_{d_\alpha} \otimes \lambda_i) & \widehat{G}_{\theta\alpha_{i,j}}(\theta, \alpha_i)' \end{pmatrix}, & \text{if } j \leq d_\alpha; \\ - \begin{pmatrix} \widehat{G}_{\theta\alpha_i}(\theta, \alpha_i)'(I_{d_\alpha} \otimes e_{j-d_\alpha}) & 0 \end{pmatrix}, & \text{if } j > d_\alpha. \end{cases} \\ M_{i,j}^W &= E \left[ \widehat{M}_{i,j}^W(\theta_0, \gamma_{i0}) \right] = \begin{cases} - \begin{pmatrix} 0 & G'_{\theta\alpha_{i,j}} \end{pmatrix}, & \text{if } j \leq d_\alpha; \\ - \begin{pmatrix} G'_{\theta\alpha_i}(I_{d_\alpha} \otimes e_{j-d_\alpha}) & 0 \end{pmatrix}, & \text{if } j > d_\alpha. \end{cases}\end{aligned}$$

## Third Derivatives

$$\begin{aligned}\widehat{M}_{i,jk}^W(\theta, \gamma_i) &= \frac{\partial^3 \widehat{s}_i^W(\theta, \gamma_i)}{\partial \gamma_{i,k} \partial \gamma_{i,j} \partial \gamma_i'} = \begin{cases} - \begin{pmatrix} \widehat{G}_{\theta\alpha, \alpha_{i,jk}}(\theta, \alpha_i)'(I_{d_\alpha} \otimes \lambda_i) & \widehat{G}_{\theta\alpha_{i,jk}}(\theta, \alpha_i)' \end{pmatrix}, & \text{if } j \leq d_\alpha, k \leq d_\alpha; \\ - \begin{pmatrix} \widehat{G}_{\theta\alpha, \alpha_{i,j}}(\theta, \alpha_i)'(I_{d_\alpha} \otimes e_{k-d_\alpha}) & 0 \end{pmatrix}, & \text{if } j \leq d_\alpha, k > d_\alpha; \\ - \begin{pmatrix} \widehat{G}_{\theta\alpha, \alpha_{i,k}}(\theta, \alpha_i)'(I_{d_\alpha} \otimes e_{j-d_\alpha}) & 0 \end{pmatrix}, & \text{if } j > d_\alpha, k \leq d_\alpha; \\ - \begin{pmatrix} 0 & 0 \end{pmatrix}, & \text{if } j > d_\alpha, k > d_\alpha. \end{cases} \\ M_{i,jk}^W &= E \left[ \widehat{M}_{i,jk}^W \right] = \begin{cases} - \begin{pmatrix} 0 & G'_{\theta\alpha_{i,jk}} \end{pmatrix}, & \text{if } j \leq d_\alpha, k \leq d_\alpha; \\ - \begin{pmatrix} G'_{\theta\alpha, \alpha_{i,j}}(I_{d_\alpha} \otimes e_{k-d_\alpha}) & 0 \end{pmatrix}, & \text{if } j \leq d_\alpha, k > d_\alpha; \\ - \begin{pmatrix} G'_{\theta\alpha, \alpha_{i,k}}(I_{d_\alpha} \otimes e_{j-d_\alpha}) & 0 \end{pmatrix}, & \text{if } j > d_\alpha, k \leq d_\alpha; \\ - \begin{pmatrix} 0 & 0 \end{pmatrix}, & \text{if } j > d_\alpha, k > d_\alpha. \end{cases}\end{aligned}$$

### G.2.3. Derivatives with respect to the common parameters.

#### First Derivatives

$$\begin{aligned}\widehat{S}_{i,j}^W(\theta, \gamma_i) &= \frac{\partial \widehat{s}_i^W(\theta, \gamma_i)}{\partial \theta_j} = -\widehat{G}_{\theta\theta_{i,j}}(\theta, \alpha_i)' \lambda_i. \\ S_{i,j}^W &= E \left[ \widehat{S}_{i,j}^W \right] = 0.\end{aligned}$$

## G.3. Two-Step Score and Derivatives: Fixed Effects.

### G.3.1. Score.

$$\begin{aligned}\widehat{t}_i(\theta, \gamma_i) &= -\frac{1}{T} \sum_{t=1}^T \begin{pmatrix} G_{\alpha_i}(z_{it}; \theta, \alpha_i)' \lambda_i \\ g(z_{it}; \theta, \alpha_i) + \widehat{\Omega}_i(\widehat{\theta}, \widehat{\alpha}_i) \lambda_i \end{pmatrix} = - \begin{pmatrix} \widehat{G}_{\alpha_i}(\theta, \alpha_i)' \lambda_i \\ \widehat{g}_i(\theta, \alpha_i) + \Omega_i \lambda_i \end{pmatrix} - \begin{pmatrix} 0 \\ (\widehat{\Omega}_i - \Omega_i) \lambda_i \end{pmatrix} \\ &= \widehat{t}_i^\Omega(\theta, \gamma_i) + \widehat{t}_i^R(\theta, \gamma_i).\end{aligned}$$

Note that the formulae for the derivatives of Appendix G.1 apply for  $\widehat{t}_i^\Omega$ , replacing  $\widehat{W}$  by  $\Omega$ . Hence, we only need to derive the derivatives for  $\widehat{t}_i^R$ .

### G.3.2. Derivatives with respect to the fixed effects.

#### First Derivatives

$$\begin{aligned}\widehat{T}_i^R(\theta, \gamma_i) &= \frac{\partial \widehat{t}_i^R(\theta, \gamma_i)}{\partial \gamma_i'} = - \begin{pmatrix} 0 & 0 \\ 0 & \widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i) - \Omega_i \end{pmatrix}. \\ T_i^R &= E[\widehat{T}_i^R] = - \begin{pmatrix} 0 & 0 \\ 0 & E[\widehat{\Omega}_i - \Omega_i] \end{pmatrix}.\end{aligned}$$

#### Second and Third Derivatives

Since  $\widehat{T}_i^R(\gamma_i, \theta)$  does not depend on  $\gamma_i$ , the derivatives (and its expectation) of order greater than one are zero.

### G.3.3. Derivatives with respect to the common parameters.

#### First Derivatives

$$\widehat{N}_i^R(\theta, \gamma_i) = \frac{\partial \widehat{t}_i^R(\theta, \gamma_i)}{\partial \theta'} = 0.$$

### G.4. Two-Step Score and Derivatives: Common Parameters.

#### G.4.1. Score.

$$\widehat{s}_i(\theta, \gamma_i) = -\frac{1}{T} \sum_{t=1}^T G_\theta(z_{it}; \theta, \alpha_i)' \lambda_i = -\widehat{G}_{\theta_i}(\theta, \alpha_i)' \lambda_i.$$

Since this score does not depend explicitly on  $\widehat{\Omega}_i(\tilde{\theta}, \tilde{\alpha}_i)$ , the formulae for the derivatives are the same as in Appendix G.2.

## REFERENCES

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Table A1: Common Parameter  $\theta_2$

Estimator	$\rho_1 = 0$				$\rho_1 = 0.3$				$\rho_1 = 0.6$				$\rho_1 = 0.9$			
	Bias	SD	SE/SD	p;.05	Bias	SD	SE/SD	p;.05	Bias	SD	SE/SD	p;.05	Bias	SD	SE/SD	p;.05
$\psi = 2$																
<i>OLS – FC</i>	0.06	0.01	0.84	1.00	0.06	0.01	0.83	1.00	0.06	0.01	0.84	1.00	0.07	0.01	0.71	1.00
<i>IV – FC</i>	0.00	0.01	0.90	0.08	-0.01	0.02	0.84	0.11	-0.01	0.02	0.78	0.18	-0.01	0.02	0.63	0.28
<i>OLS – RC</i>	0.04	0.01	0.97	1.00	0.04	0.01	0.99	1.00	0.04	0.01	1.02	1.00	0.04	0.01	0.96	1.00
<i>BC – OLS</i>	0.04	0.01	0.97	1.00	0.04	0.01	0.99	1.00	0.04	0.01	1.02	1.00	0.04	0.01	0.96	1.00
<i>IBC – OLS</i>	0.04	0.01	0.97	1.00	0.04	0.01	0.99	1.00	0.04	0.01	1.02	1.00	0.04	0.01	0.96	1.00
<i>IV – RC</i>	0.00	0.01	1.00	0.06	0.00	0.01	1.01	0.05	0.00	0.01	1.00	0.05	0.00	0.01	1.01	0.05
<i>BC – IV</i>	0.00	0.01	0.99	0.06	0.00	0.01	1.01	0.05	0.00	0.01	1.00	0.05	0.00	0.01	1.00	0.05
<i>IBC – IV</i>	0.00	0.01	0.99	0.06	0.00	0.01	1.01	0.05	0.00	0.01	1.00	0.05	0.00	0.01	1.00	0.05
$\psi = 4$																
<i>OLS – FC</i>	0.12	0.01	1.09	1.00	0.12	0.01	1.03	1.00	0.12	0.01	1.10	1.00	0.12	0.01	1.07	1.00
<i>IV – FC</i>	0.00	0.02	0.94	0.07	-0.01	0.02	0.89	0.08	-0.01	0.02	0.92	0.09	-0.01	0.03	0.79	0.15
<i>OLS – RC</i>	0.10	0.01	1.06	1.00	0.10	0.01	1.05	1.00	0.11	0.01	1.08	1.00	0.11	0.01	1.07	1.00
<i>BC – OLS</i>	0.10	0.01	1.06	1.00	0.10	0.01	1.05	1.00	0.11	0.01	1.08	1.00	0.11	0.01	1.07	1.00
<i>IBC – OLS</i>	0.10	0.01	1.06	1.00	0.10	0.01	1.05	1.00	0.11	0.01	1.08	1.00	0.11	0.01	1.07	1.00
<i>IV – RC</i>	0.00	0.02	0.98	0.06	0.00	0.02	0.96	0.06	0.00	0.02	1.01	0.05	0.00	0.02	1.00	0.06
<i>BC – IV</i>	0.00	0.02	0.97	0.05	0.00	0.02	0.95	0.06	0.00	0.02	1.00	0.05	0.00	0.02	0.99	0.06
<i>IBC – IV</i>	0.00	0.02	0.97	0.05	0.00	0.02	0.95	0.06	0.00	0.02	1.00	0.05	0.00	0.02	0.99	0.06
$\psi = 6$																
<i>OLS – FC</i>	0.16	0.01	1.27	1.00	0.16	0.01	1.22	1.00	0.16	0.01	1.25	1.00	0.16	0.01	1.34	1.00
<i>IV – FC</i>	0.00	0.03	0.95	0.06	0.00	0.03	0.94	0.06	-0.01	0.03	0.92	0.08	-0.01	0.04	0.92	0.08
<i>OLS – RC</i>	0.15	0.01	1.20	1.00	0.15	0.01	1.21	1.00	0.15	0.01	1.21	1.00	0.15	0.01	1.26	1.00
<i>BC – OLS</i>	0.15	0.01	1.20	1.00	0.15	0.01	1.21	1.00	0.15	0.01	1.21	1.00	0.15	0.01	1.26	1.00
<i>IBC – OLS</i>	0.15	0.01	1.20	1.00	0.15	0.01	1.21	1.00	0.15	0.01	1.21	1.00	0.15	0.01	1.26	1.00
<i>IV – RC</i>	0.00	0.03	0.98	0.06	0.00	0.03	1.00	0.04	0.00	0.03	1.01	0.05	0.00	0.03	1.05	0.04
<i>BC – IV</i>	0.00	0.03	0.95	0.06	0.00	0.03	0.97	0.04	0.00	0.03	0.98	0.05	0.00	0.03	1.02	0.04
<i>IBC – IV</i>	0.00	0.03	0.95	0.06	0.00	0.03	0.97	0.04	0.00	0.03	0.98	0.05	0.00	0.03	1.02	0.04

RC/FC refers to random/fixed coefficient model. BC/IBC refers to bias corrected/iterated bias corrected estimates.

Note: 1,000 repetitions.

**Table A2: Mean of Individual Specific Parameter  $\mu_1 = \bar{E}[\alpha_{1i}]$**

Estimator	$\rho_1 = 0$				$\rho_1 = 0.3$				$\rho_1 = 0.6$				$\rho_1 = 0.9$			
	Bias	SD	SE/SD	p;.05	Bias	SD	SE/SD	p;.05	Bias	SD	SE/SD	p;.05	Bias	SD	SE/SD	p;.05
$\psi = 2$																
<i>OLS – FC</i>	2.33	1.65	0.35	0.78	2.58	1.91	0.31	0.79	3.01	1.92	0.30	0.84	3.68	2.20	0.27	0.89
<i>IV – FC</i>	0.08	1.59	0.40	0.44	0.16	1.72	0.37	0.47	0.46	1.66	0.39	0.46	0.96	1.80	0.37	0.53
<i>OLS – RC</i>	1.16	1.53	1.02	0.12	1.15	1.65	0.96	0.12	1.19	1.59	0.99	0.12	1.25	1.62	0.97	0.13
<i>BC – OLS</i>	1.16	1.53	0.97	0.14	1.15	1.65	0.92	0.14	1.19	1.59	0.95	0.14	1.25	1.62	0.93	0.15
<i>IBC – OLS</i>	1.16	1.53	0.97	0.14	1.15	1.65	0.92	0.14	1.19	1.59	0.95	0.14	1.25	1.62	0.93	0.15
<i>IV – RC</i>	0.01	1.51	1.07	0.04	-0.01	1.62	1.00	0.05	0.02	1.56	1.04	0.05	0.08	1.59	1.03	0.05
<i>BC – IV</i>	-0.01	1.51	1.02	0.04	-0.02	1.62	0.96	0.06	0.00	1.56	1.00	0.06	0.06	1.59	0.98	0.06
<i>IBC – IV</i>	-0.01	1.51	1.02	0.04	-0.03	1.62	0.96	0.06	0.00	1.56	1.00	0.06	0.06	1.59	0.98	0.06
$\psi = 4$																
<i>OLS – FC</i>	4.15	1.84	0.52	0.90	4.43	1.95	0.49	0.90	4.90	2.08	0.46	0.93	5.45	2.22	0.43	0.95
<i>IV – FC</i>	0.09	1.85	0.59	0.25	0.21	1.92	0.57	0.27	0.56	1.89	0.58	0.27	1.03	1.94	0.57	0.32
<i>OLS – RC</i>	3.19	1.76	1.06	0.41	3.12	1.81	1.04	0.38	3.12	1.76	1.07	0.38	3.18	1.78	1.06	0.38
<i>BC – OLS</i>	3.19	1.76	0.93	0.50	3.12	1.81	0.91	0.48	3.12	1.76	0.94	0.47	3.18	1.78	0.93	0.47
<i>IBC – OLS</i>	3.19	1.76	0.93	0.50	3.12	1.81	0.91	0.48	3.12	1.76	0.94	0.47	3.18	1.78	0.93	0.47
<i>IV – RC</i>	0.06	1.78	1.15	0.03	-0.01	1.86	1.10	0.03	0.03	1.78	1.15	0.03	0.10	1.78	1.15	0.03
<i>BC – IV</i>	0.00	1.78	1.02	0.05	-0.08	1.86	0.98	0.05	-0.04	1.78	1.02	0.05	0.03	1.78	1.02	0.05
<i>IBC – IV</i>	-0.01	1.78	1.02	0.05	-0.08	1.86	0.98	0.05	-0.04	1.78	1.02	0.05	0.03	1.78	1.02	0.05
$\psi = 6$																
<i>OLS – FC</i>	5.62	2.13	0.62	0.93	5.87	2.25	0.58	0.92	6.19	2.31	0.57	0.93	6.35	2.28	0.57	0.95
<i>IV – FC</i>	0.14	2.29	0.69	0.17	0.26	2.34	0.68	0.19	0.53	2.31	0.69	0.19	0.80	2.26	0.70	0.20
<i>OLS – RC</i>	4.69	2.10	1.08	0.53	4.59	2.14	1.07	0.51	4.52	2.11	1.09	0.50	4.30	2.01	1.15	0.46
<i>BC – OLS</i>	4.69	2.10	0.88	0.69	4.59	2.14	0.88	0.67	4.52	2.11	0.89	0.64	4.30	2.01	0.94	0.61
<i>IBC – OLS</i>	4.69	2.10	0.88	0.69	4.59	2.14	0.88	0.67	4.52	2.11	0.89	0.64	4.30	2.01	0.94	0.61
<i>IV – RC</i>	0.09	2.30	1.12	0.04	0.05	2.33	1.11	0.03	0.03	2.23	1.16	0.02	-0.10	2.18	1.19	0.02
<i>BC – IV</i>	-0.05	2.30	0.95	0.06	-0.10	2.33	0.94	0.06	-0.12	2.23	0.97	0.06	-0.26	2.18	1.00	0.05
<i>IBC – IV</i>	-0.06	2.30	0.95	0.06	-0.10	2.32	0.94	0.06	-0.13	2.23	0.97	0.06	-0.26	2.18	1.00	0.05

RC/FC refers to random/fixed coefficient model. BC/IBC refers to bias corrected/iterated bias corrected estimates.

Note: 1,000 repetitions.

**Table A3: Standard Deviation of the Individual Specific Parameter  $\sigma_1 = \bar{E}[(\alpha_{1i} - \mu_1)^2]^{1/2}$**

Estimator	$\rho_1 = 0$				$\rho_1 = 0.3$				$\rho_1 = 0.6$				$\rho_1 = 0.9$			
	Bias	SD	SE/SD	p;.05	Bias	SD	SE/SD	p;.05	Bias	SD	SE/SD	p;.05	Bias	SD	SE/SD	p;.05
$\psi = 2$																
<i>OLS – RC</i>	0.01	1.06	1.02	0.05	0.15	1.06	1.02	0.05	0.11	1.08	0.99	0.06	0.17	1.06	0.99	0.06
<i>BC – OLS</i>	-0.63	1.10	1.04	0.10	-0.48	1.11	1.04	0.09	-0.52	1.12	1.01	0.10	-0.46	1.11	1.01	0.09
<i>IBC – OLS</i>	-0.63	1.10	1.04	0.10	-0.48	1.11	1.04	0.09	-0.52	1.12	1.01	0.10	-0.46	1.11	1.01	0.09
<i>IV – RC</i>	0.38	1.08	1.03	0.05	0.47	1.10	1.02	0.06	0.41	1.13	0.98	0.06	0.46	1.11	0.99	0.06
<i>BC – IV</i>	-0.25	1.13	1.05	0.06	-0.16	1.14	1.04	0.06	-0.22	1.18	1.00	0.07	-0.17	1.16	1.00	0.06
<i>IBC – IV</i>	-0.25	1.13	1.05	0.06	-0.16	1.14	1.04	0.06	-0.22	1.18	1.00	0.07	-0.17	1.16	1.00	0.06
$\psi = 4$																
<i>OLS – RC</i>	0.89	1.21	1.17	0.04	0.98	1.20	1.17	0.05	1.08	1.16	1.19	0.06	1.09	1.05	1.23	0.08
<i>BC – OLS</i>	-1.24	1.46	1.19	0.08	-1.13	1.44	1.20	0.08	-1.02	1.41	1.20	0.05	-0.98	1.23	1.24	0.03
<i>IBC – OLS</i>	-1.24	1.46	1.19	0.08	-1.13	1.44	1.20	0.08	-1.02	1.41	1.20	0.05	-0.98	1.24	1.22	0.03
<i>IV – RC</i>	1.84	1.28	1.17	0.17	1.83	1.29	1.16	0.16	1.85	1.26	1.17	0.18	1.87	1.18	1.17	0.20
<i>BC – IV</i>	-0.25	1.52	1.20	0.03	-0.26	1.52	1.19	0.02	-0.26	1.51	1.18	0.03	-0.21	1.37	1.18	0.02
<i>IBC – IV</i>	-0.25	1.52	1.20	0.03	-0.26	1.52	1.19	0.02	-0.26	1.51	1.18	0.03	-0.21	1.38	1.16	0.02
$\psi = 6$																
<i>OLS – RC</i>	2.35	1.33	1.38	0.14	2.60	1.40	1.30	0.21	2.57	1.37	1.31	0.21	2.69	1.31	1.28	0.38
<i>BC – OLS</i>	-2.06	2.04	1.41	0.00	-1.71	2.14	1.30	0.01	-1.75	2.06	1.35	0.00	-1.54	1.78	1.28	0.00
<i>IBC – OLS</i>	-2.06	2.04	1.41	0.00	-1.71	2.14	1.30	0.01	-1.75	2.06	1.35	0.00	-1.54	1.80	1.26	0.00
<i>IV – RC</i>	3.79	1.52	1.31	0.46	3.87	1.55	1.28	0.49	3.78	1.50	1.30	0.47	3.87	1.48	1.23	0.60
<i>BC – IV</i>	-0.49	2.13	1.37	0.00	-0.42	2.23	1.29	0.01	-0.55	2.14	1.35	0.00	-0.40	1.96	1.24	0.01
<i>IBC – IV</i>	-0.49	2.13	1.37	0.00	-0.41	2.23	1.29	0.01	-0.55	2.14	1.35	0.00	-0.39	1.97	1.22	0.02

RC/FC refers to random/fixed coefficient model. BC/IBC refers to bias corrected/iterated bias corrected estimates.

Note: 1,000 repetitions.